A PARETO FRONTIER WELL PLACEMENT AND RATE OPTIMIZATION

BY

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To my beloved, helpful and supportive family, Petroleum Engineering faculty, friends and colleagues.

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LIST OF ABBREVIATIONS

N_{obj}	:	Number of objective functions
w_i	:	Weighting factor
c_i	:	Scaling factor
d_c	:	Minimal distance between clusters
NPV	:	Net present value
VRR	:	Voidage replacement ratio
VIR	:	Voidage imbalance ratio
N_p	:	Population size
F	:	Mutation factor
CR	:	Crossover factor
n	:	Period index
C_{cap}	:	Capital expenses
$C_{facility}$	:	Facility installation cost
N_{prod}	:	Number of producers
C_{prod}	:	cost of drilling one production well
N_{inj}	:	Number of injectors
C_{inj}	:	Cost of drilling one injection well
CF_n	:	Cash flow
R_n	:	Total revenue
P^o_n	:	Oil price
$Q_n^{o,prod}$	:	Total produced oil
E_n	:	Total operating expenditure

$C_n^{w, prod}$	:	Cost of treating/disposing the produced water
$Q_n^{w, prod}$	:	Total produced water
$C_n^{w, inj}$	:	Cost of acquiring and treating the injected water
$Q_n^{w, inj}$	:	Total injected water
$C_{op, n}$	:	Operating cost
r	:	Annual discount rate
$B_{w,n}$	:	Average formation volume factor for water
$B_{o,n}$	:	Average formation volume factor for oil
$B_{g,n}$	:	Average formation volume factor for gas
GOR_n	:	Cumulative gas oil ratio
$R_{so,n}$	:	Solution gas oil ratio
S_w	:	Water saturation
K_{rw}	:	Relative permeability for water
K_{ro}	:	Relative permeability for oil
μ_o	:	Oil viscosity

ABSTRACT

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Selection of crucial decision variables such as well placement and rates can enhance the extraction of hydrocarbon resources and subsurface energy.

Identification of well locations is a significant part in field development plan. A field performance can be impaired if appropriate well coordinates are not selected which is an intricate challenge that depends on the properties of reservoir and fluids, surface and subsurface equipment specifications, and the economical norms. Therefore well placement optimization is required for effective reservoir performance.

In addition to identifying optimal well locations, one needs to specify the best operational settings (working fluid rates) for each well to optimize the performance of the whole system.

Various approaches have been proposed for determining the best well locations and/or operating rates. Among those, only the economic performance is considered regardless of the environmental issues. An exception is a research done to study the combination of economic and environmental factors using net present value and voidage replacement ratio. However, that approach used the aggregation method in which all objective functions are summed together with scaling factor to act as a single objective function. This brings another challenge to specify the appropriate scaling factor.

To overcome the previous problem, this thesis considered and performed multiobjective optimization of well placement, operating rates and simultaneous optimization of well locations and dynamic rate allocations using differential evolution algorithm for multiobjective with Pareto rank. In this method, the optimal set of alternative solutions is detected instead of one global solution as in single objective optimization. By this, different options are provided for the decision makers. Net present value and voidage replacement ratio were served as the fitness values (objective functions). MATLAB was used for this optimization and Eclipse reservoir simulator was used for evaluating the fitness of alternative solutions.

Two different synthetic cases are presented to show the usefulness of the approach and analyses of how investors can make use of the Pareto-optimal well locations and rates in field development planning.

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الاسم الكامل : أشرف هاشم بابكر أحمد

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لا شك في أن اختيار المتغيرات الحاسمة مثل موضع ومعدلات الانتاج والحقن للآبار بشكل جيد يعزز تنمية الموارد البيئية والطاقة الجوفية لتحسين أداء الحقل حيث أنه من الممكن أن ينخفض أداء الحقول إذا لم يتم تحديد الإحداثيات ومعدلات التشغيل المناسبة للآبار حيث أن كيفية تحديدها معقدة وتعتمد على خصائص المكمن والموائع ومواصفات المعدات السطحية وتحت السطحية والمعايير الاقتصادية. لذا لضمان أداء فعال يتعين تحديد مواضع الآبار ومعدلات تشغيلها.

لقد تم تطوير العديد من الابحاث والتقنيات لتحديد أفضل المواقع ومعدلات الانتاج والحقن للآبار مجتمعين أو كل علي حدة، إلا أن هذه التقنيات درست فقط التأثير الاقتصادي بغض النظر عن الأثر البيئي باستثناء البحث الذي أجري لدراسة تأثير معدل الافراغ والاحلال كعامل بيئي بجانب المعايير الاقتصادية إلا أن التقنية المستخدمة في تلك الدراسة تعتمد أسلوب الجمع المرجح حيث يتم دمج جميع دوال الهدف باستخدام وزن و عامل تحجيم معينين لتصبح بمثابة دالة هدف واحدة وهو ما يعني تحدياً آخر في تحديد هذه العوامل بطريقة مناسبة.

لحل وتلافي السلبيات والمعوقات في الابحاث السابقة فإن هذا البحث قد درس ثلاث سيناريوهات: السيناريو الاول يشمل كيفية تحديد الموضع الأمثل للآبار والسيناريو الثاني درس ايجاد معدلات التشغيل المناسبة للآبار أما في الثالث فقد تم دمج السيناريوهين الأولين ليتم تحديدهما في آن واحد حيث يتم تحسين عدة دوال هدف وذلك باستخدام خوارزمية التطور التفاضلية مع ترتيب باريتو. في هذه التقنية يتم تحسين جميع دوال الهدف آنياً دون دمجها وينتج عن ذلك مجموعة من الحلول المحسنة بدلاً من حل واحد كما هو الحال في تحسين دالة هدف واحدة وبالتالي يتم اقتراح عدة خيارات محسنة لصانعي القرار مع الأخذ في الاعتبار كل من الجوانب البيئية ممثلة في معدل الافراغ والاحلال والجوانب الاقتصادية ممثلة في صافي القيمة الحالية. في هذه الدراسة تم استخدام برنامج ماتلاب وبرنامج لمحاكاة المكامن.

استخدم في هذه الدراسة مثالين افتراضيين لإظهار جدوى هذه التقنية، وقد تم عرض النتائج والتحليلات التي تبين كيفية استفادة المستثمرين من هذه التقنية في التخطيط لتنمية وتطوير الحقل.

CHAPTER 1

INTRODUCTION

1.1 Introduction

The determination of the optimum well allocations and/or the operating conditions is a relatively new area of study. Since the 1980's many studies have been conducted with various optimization algorithms that resulted in different useful techniques. All these approaches considered the economic value as the main effect. Accordingly, the net present value, NPV is used to define the profitability of any project, so it served as the fitness value for the optimization problem.

Although the models which depend upon single objective optimization are adequate for some approaches, there are numerous conditions where multiobjective optimization (MOBJ) must be considered. In MOBJ, the target is to simultaneously optimize a collection of objective functions that are conflicting with one another.

Most real optimization problems have multiobjective nature, so this multiple objectives optimization is a significant research subject and becoming more important in diverse fields and has vast implementations. Actually, no global definition of "optimum" has been admitted in multiple objectives optimization problems because there is no single optimal solution as contrary to problems of single objective optimization. But rather, a group of alternative solutions which is named the Pareto frontier or optimal Pareto set.

When considering all objective functions of the problem, every solution in this optimal Pareto set is superior in some sense to all other solutions in the search space. Normally, the decision about the "best" solution coincides to the professed human decision-maker.

The notion of multiobjective optimization can be applied to define the optimum coordinates of well locations and the corresponding operating rates by maximizing the net present value and improving the voidage replacement ratio.

Maximizing production from an oil field and reducing the environmental concerns are crucial tasks, given the enormous financial investment at stake in any large-scale field development. Decisions regarding the placement of new wells, and control of injection and production rates at existing wells, have a significant impact on production. Poor placement and/or control of wells may result in premature water breakthrough at the production wells, or make it difficult to achieve high flow rates while maintaining reservoir pressure.

1.2 Statement of the Problem

In optimizing well placement and well controls, simultaneously satisfying the investors and environmental agencies can be difficult. The difficulty arises from the fact that enforcing environmental regulations often have negative impact on economic returns. Thus, a balance between ensuring profitability of investment and keeping to environmental regulations must be found. The net present value, NPV is often used as an indicator of economic performance while the voidage replacement ratio, VRR is one of the factors used as an indicator of environmental safety.

Recently, a study was conducted by Awotunde and Sibaweihi proposing the use of a weighted combination of the NPV and VRR as an objective function in well placement optimization (Awotunde and Sibaweihi 2014). This approach proved effective in integrating both objectives in the determination of the optimum well placement. The approach however, requires that users determine a priori the weights to put on each objective.

In this work, we present a Pareto-based multiobjective approach for integrating the NPV and the VRR in three optimization scenarios to ensure high NPV and acceptable VRR. In the first scenario, only well placement optimization is studied. The second scenario considers only well rate optimization and the third scenario consists of optimizing simultaneously well placement and well rate. The Pareto approach allows us to obtain several optimal instances of well locations and/or well rates, each instance optimal in a particular sense. Differential evolution was used as an optimizer and well spacing constraints were enforced. A set of Pareto-optimal was obtained in each optimization framework and this set forms a Pareto front from which decisions can be made. The advantage of this method is that it allows investor to look at a wide variety of possibilities for well placement and/or operating rate each possibility being optimal with respect to the NPV and VRR in some sense.

1.3 Research Objectives

The major goals of this research include the following:

1. Examining the success of the multiobjective differential evolution algorithm with Pareto ranking.

2. Using the proposed technique to find the optimum well placement.
3. Using the same method to optimize the operating condition (well rates).
4. Optimizing well locations and operating rates simultaneously.

1.4 Research Methodology

In this thesis, we carried out optimization study that comprised optimizing well placement and well operating rate using multiobjective differential evolution algorithm with Pareto ranking. The optimization problems are solved for three scenarios; the first scenario focused only on finding the optimum (x,y)-configurations for all producers and injectors, whereas the second concentrated on optimizing the well control settings (operating rates) assuming the wells had already been located. Lastly, simultaneous optimization of well locations and dynamic rate allocations was considered. In each scenario, four cases are studied as shown in Figure 1.1. Firstly, only NPV is considered, secondly, only VRR, then, optimizing a combination of them using a weighted sum technique with equal weights and finally, both NPV and VRR are optimized using Pareto-based technique. The research methodology included:

- Preparing the input files for Eclipse reservoir simulation.
- Developing and employing code for DE algorithm for multiobjective in MATLAB.
- Developing and integrating code for Pareto ranking with DE algorithm.
- Writing code to connect Eclipse simulator to MATLAB.
- Developing objective functions file in MATLAB.
- Developing and employing well spacing constraints to avoid the problem of locating different wells in the same location.

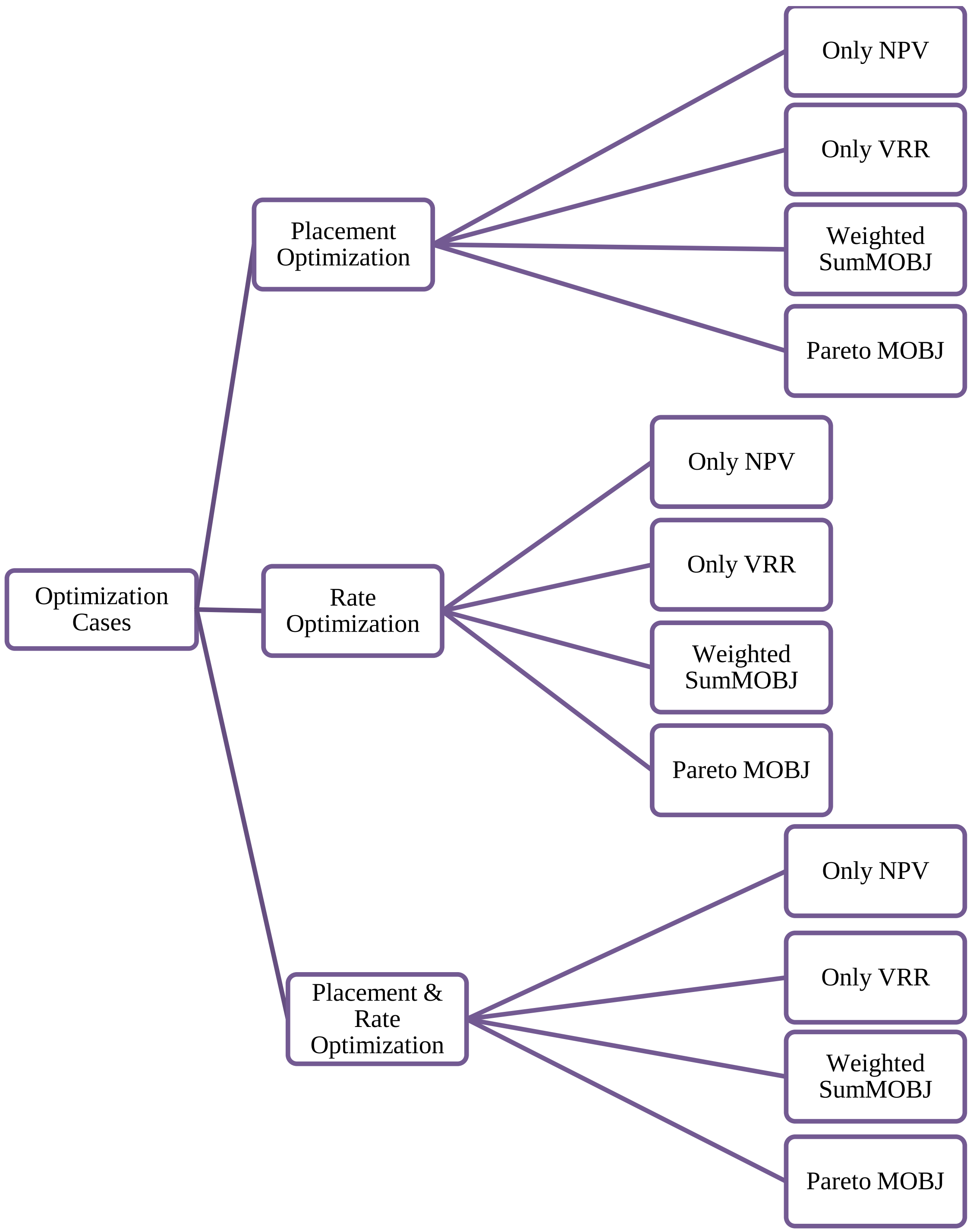

Figure 1.1: Optimization cases

CHAPTER 2

LITERATURE REVIEW

Optimization is a common area of concern for all engineering disciplines. In general, there are two broad categories of optimization; stochastic and deterministic. Deterministic methods are based on the concept of successive search within the optimization space, based on the function gradient information. The step is taken in the direction in which the function is optimized (minimized or maximized). These methods use the strategy of finding the next iteration based on derivative information, they only yield good results with functions which are continuous, convex and unimodal. In engineering sciences, the problems are usually complex, non-linear, and are sometimes described by non-differentiable functions, demanding more efficient numerical methods for their solution. In these types of problems, stochastic methods are employed. Stochastic methods search for the optimal solution of a certain problem using an "oriented random" approach and the iterative improvement of a population of solutions. These techniques are categorized as meta-heuristics which mostly employ randomization to solve a given optimization problem. Figure 2.1 shows taxonomy of various optimization algorithms.

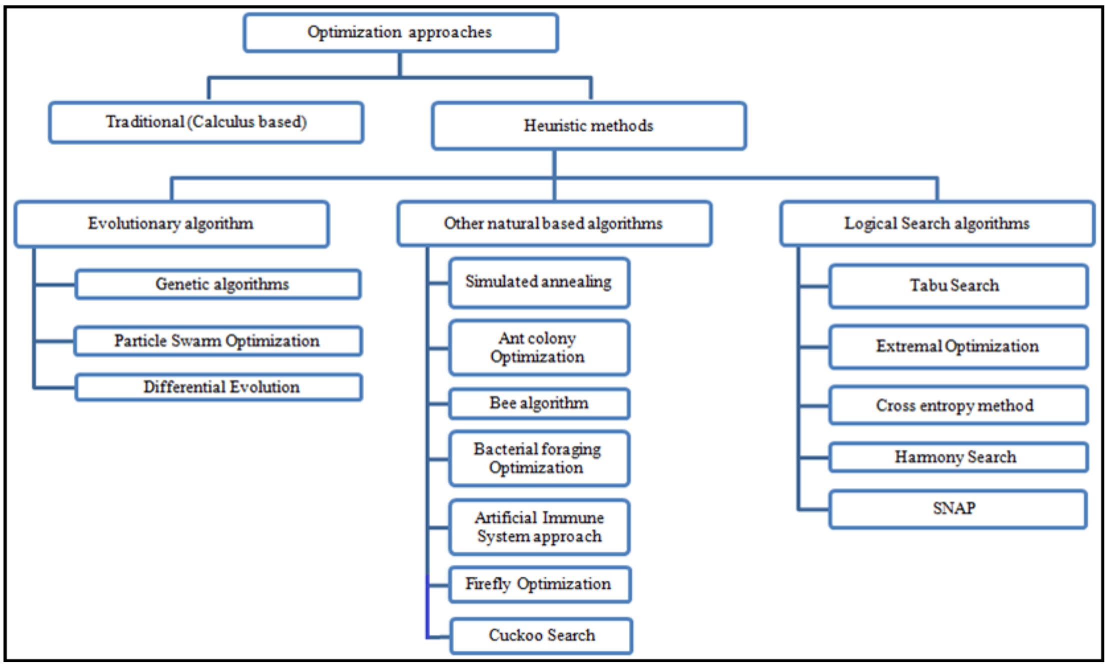

Figure 2.1: Taxonomy of various optimization algorithms

The concept of optimization in reservoir engineering became very important because most of the hydrocarbons producing fields worldwide are mature, hence a need for reservoir engineers to optimize the reservoir performance. In this context, one of the critical and challenging problems is the efficient placement of the wells in the reservoir in addition to the optimum operating conditions of these wells. Many variables can dictate the decision for well placement which includes reservoir rock and fluid properties such as permeability, porosity, reservoir architecture, reservoir heterogeneity, well type, production rates, and economic criteria. After thorough understanding of these variables, following questions can be answered (Gűyagűler et al. 2000, Ding 2008, Bukhamsin et al. 2010, Forouzanfar et al. 2010)

- What will be the well type (vertical, horizontal or multilateral)?
- In case of horizontal well, what will be the length of the horizontal section?
- In which direction the horizontal well should be drilled?
- In case of multilateral well, how many laterals are needed and what are their lengths and directions?
- What will be the depth and type of completion?

Researchers found non-gradient based optimization techniques as an efficient tool for well placement optimization (Bittencourt and Horne 1997, Yeten et al. 2002, Bangerth et al. 2006, Ozdogan and Horne 2006, Emerick et al. 2009).

In recent years, many studies presented different optimization methods to couple well rate with well placement optimization (Brouwer and Jansen 2004, Handels et al. 2007

Wang et al. 2007, Sarma and Chen 2008, Zandvliet et al. 2008, Bellout et al. 2011, Li et al. 2012, Mathias et al. 2012).

The development of efficient adjoint techniques for calculating the gradients of well production responses to well control variables has led to a number of creative attempts to approximate the gradients regarding well locations using pseudo wells and adjoint methods (Handels et al. 2007, Wang et al. 2007, Sarma and Chen 2008).

In this approach, pseudo wells are placed in the immediate neighboring grid blocks to each major well in the reservoir domain. The pseudo wells are wells of the same type as the major target wells in the simulation (injection or production) with sufficiently low flow rates to minimize their effect on the simulation results. The standard adjoint method is then applied to find the gradient of the objective function respecting pseudo-well rates. At each iteration, among the pseudo wells surrounding each major well, the one with maximum gradient is used to approximate an ascent direction for well placement optimization (that is, the major well is shifted to the site of the neighboring pseudo-well with the largest gradient) (Handels et al. 2007).

A correct interpretation of the adjoint-based gradient information in the pseudo-well approach is in fact different from the gradients needed for well placement. To improve the previous gradient definition, Sarma and Chen proposed that the Dirac delta function representing the well (sink/source) terms in reservoir simulation be approximated by a multivariate Gaussian function (describing the spatial distribution and rates of many pseudo wells around the major target wells). After adopting this modification, the adjoint method is used to first find the gradient of the objective function with respect to pseudo well rates and then convert them to the gradients with respect to well locations using the chain rule of differentiation and the functional relation between pseudo-well locations and rates.

Wang et al also used a gradient-based well placement optimization where they started the optimization by placing one well with constant rate in all grid blocks and iteratively removed the wells based on the gradient information to improve the objective function that accounted for drilling costs. In this approach, the discrete variables (i.e., well locations) are replaced with continuous decision variables (i.e., well rates) and whether a grid block is a good candidate for drilling a well is inferred from the rates. The numerical experiments presented in (Handels et al. 2007, Wang et al. 2007, Sarma and Chen 2008) suggest that, despite the approximations involved, adjoint-based gradients provide reasonable ascent directions for well placement optimization.

Within reservoir engineering context, gradient based methods can only be efficient if efficient adjoint models are applied to compute the gradients. However, constructing an adjoint model is a relatively involved process that requires additional development in the forward modeling source codes. An alternative approach is the stochastic optimization method.

In particular, the simultaneous perturbation stochastic approximation (SPSA) has been developed for use with large dimensional multivariate optimization problems in several applications where the gradient information is not available and when the objective function can be noisy. In order Li et al used a version of the SPSA algorithm for solving the coupled optimization of well placement and dynamic rate (Li et al. 2012).

In recent times, economic studies have been carried out and selection criterions have been developed for well type, performance, and placement selection. Feasibility analysis have been done for the placement of horizontal and vertical wells in the reservoir (Aanonsen et al. 1995, Dejean and Blanc 1999, Yeten et al. 2002, Badru and Kabir 2003, Gűyagűlar 2003, Nakajima and Schoizer 2003, Seifi and Kazemzadeh 2008, Hassani et al. 2011). Different optimization methodologies have been used for the determination of optimum location of these wells. The techniques used are response surface methodology (Aanonsen et al. 1995, Dejean and Blanc 1999, Hassani et al. 2011) and meta-modeling based methodology (Seifi and Kazemzadeh 2008, Hassani et al. 2011). Furthermore, multiple optimization techniques are combined to form a single hybridized algorithm which improves the efficiency of the process. The techniques used in hybridization are genetic algorithm, Tabu search and Polytope algorithm (Yeten et al. 2002), Kriging proxy, neural networks, Polytope algorithm (Gűyagűlar 2003), and genetic algorithm and Polytope algorithm (Nakajima and Schoizer 2003, Badru and Kabir 2003).

Therefore, in order to address the optimization problems in well placement and rate, this research discusses evolutionary optimization algorithm namely Differential Evolution (DE). A brief characterization of this algorithm is presented hereunder.

DE is a member of evolutionary algorithms categorized under population-based stochastic global optimization. The algorithm is known for its robustness, simplicity, fewer numbers of control variables and fast convergence. The merit of DE algorithm is its singular mutation schema for vector perturbation using vector differences to produce new generation.

DE starts with the initialization of random particles (parents) within the search space. These initial particles (parents) take part in the process of mutation and crossover to come up with a new set of particles (offsprings). Mutation is done by taking difference between randomly selected vectors (parents) to generate the new solutions (offsprings). To further perturb this new solution, crossover method is used by copying offspring and its parent to a new vector named as trial vector. Using certain crossover factor, individual parameters of these solutions are perturbed and selected. Selection method is employed between the old solutions and their corresponding trial solutions by computing objective function value for trial solutions. If the latter performed better, they will be selected, otherwise the old solutions are retained (Storn 1995, Storn and Price 1995, Storn 1996, Storn and Price 1996, Lampinen and Zelinka 1999, Lampinen 2001, Karaboga and Okdem 2003, Coello et al. 2007).

In our thesis the original DE algorithm for single objective will be widened to optimize multiple objectives.

Generally, evolutionary algorithms for multiobjective optimization problems are classified into plain aggregating, non-Pareto and Pareto based techniques (Coello 1999). In the former approach a linear integration of all objective functions is taken to behave as one objective function as in goal programming, goal attainment, and the weighted summation techniques. All aggregating approaches generate only one solution which may not gratify the decision-makers and they should pre-define the importance and weight of each objective function, which is a difficult challenge in most real optimization problems. However, simultaneously optimizing all objective functions and producing multiple solutions, presents more options to decision-makers.

An example of the population based non-Pareto techniques is the so called VEGA (Vector Evaluated Genetic Algorithm). In this algorithm, the whole population is parted into a number of populations that equivalent to the objectives number, then each objective function is optimized independently using each population, after that the populations are mingled together succeeded by the mutation and crossover processes (Schaffer 1985). But the resulted solutions of this approach are locally nondominated.

In the Pareto based techniques, the nondominated and dominated solutions in the current population are segregated. Goldberg proposed a nondominated arranging process to determine the fitness of the solutions (Goldberg 1989). In 1994, Srinivas and Deb presented the NSGA (Nondominated Sorting Genetic Algorithm) founded on the concept of Goldberg's process. The individuals of the population are layered in accordance with their classes. Subsequently, the non dominated solutions are eliminated layer by layer from the population (Srinivas and Deb 1994).

Fonseca and Fleming suggested a strategy which is called the FFES (Fonseca and Fleming Evolutionary Strategy). In this technique, a solution's class is specified by the number of solutions dominating it (Fonseca and Fleming 1993). Also, Horn et al presented the NPGA (Niched Pareto Genetic Algorithm) which uses a set of solutions that are selected randomly to shape a comparison reference set. The fitness for the randomly picked solutions is determined in accordance with if they are dominated by any of the solutions from the comparison reference set. If all solutions are either dominated or nondominated by the comparison reference set, then a niched technique is applied for selection (Horn et al. 1994).

In 1999, Zitzler and Thiele presented a Pareto-based approach called the SPEA (Strength Pareto Evolutionary Algorithm). In this technique, the nondominated solutions are sorted externally and the population is updated continuously. In addition, the fitness of the solution is evaluated based on the number of exterior nondominated solutions which dominate it and the clustering procedure is applied to reduce the size of the nondominated set (Zitzler and Thiele 1999).

Further, Knowles and Corne suggested a technique called the PAES (Pareto Archived Evolution Strategy). A register of finite nondominated solutions is memorized based on the magnitude of crowdedness in the Pareto front which guarantees enough variety of solutions. But this approach is restricted to local search and problems with small dimensions (Knowles and Corne 1999, Knowles and Corne 2000).

Particularly regarding the optimization in petroleum engineering, the implementation of multiple objectives optimization techniques is scarcely done unlike other engineering areas; however the importance of considering multiobjective optimization in oil industry has been stated since 1980's. The study done by Harrison and Tweedie was the inaugural research in this aspect. They applied the weighted-sum technique to find the optimum production strategy by summing multiple economical criteria (Harrison and Tweedie 1981). Also Rahman et al applied the same technique in designing hydraulic fracturing by combining four objectives to minimize the cost and maximize the NPV and production (Rahman et al. 2001). Ray and Sarker applied different technique called NSGA-II (Nondominated Sorting Genetic Algorithm) for designing gas lift to maximize oil production and minimize gas injection (Ray and Sarker 2006). In water flooding projects, Cardoso used the weighted-sum approach to maximize the produced oil and minimize the injected water (Cardoso 2009). Moreover, multiobjective optimization approach is used in history matching problems such as the study addressed by Schulze-Riegert et al which used a technique called SPEA (Strength Pareto Evolutionary Algorithm) to find the solutions in Pareto set (Schulze-Riegert et al. 2007). Recently, the first attempt to apply the concept of multiobjective optimization in well placement was presented by Awotunde and Sibaweihi. They studied the effect of the environmental issue such as the voidage replacement ratio. In order to do this, they combined the net present value and voidage replacement ratio in multiobjective well placement optimization using the weighted sum method. Their study showed the importance and need for considering the environmental effect as well as the economic effect and so applying the concept of multiobjective optimization to define the optimum well locations. But the main drawback of the method is the need for prior knowledge of the problem to determine the optimum weights of each objective function (Awotunde and Sibaweihi 2014).

CHAPTER 3

THEORETICAL BACKGROUND

3.1 Well Placement

Well placement in the reservoir is one of the most important steps and challenging task in field development. After having a reliable geological model and reservoir characterization, the next task is to have optimum locations of injectors and producers which will fulfill the production needs as per the production plans. The conventional practice of finding the optimum location for the wells is by manually changing the position of the wells in the reservoir using reservoir simulator based on the engineering knowledge. In recent times, advancements in stochastic optimization algorithms have made it possible to automate finding the optimum locations of the wells in the reservoir with improved efficiency.

3.2 Well Rate

In a water-flooding project, the determination of well control settings like operational rates for producers and injectors in heterogeneous reservoirs is a challenging process which has a considerable influence on the economic value and environmental balance of subsurface energy resources. Water-flooding where the oil in the reservoir is driven towards production wells by a moving waterfront created by water injection wells, is a common procedure for oil production. Substantial oil volumes are often bypassed during water-flooding due to the existence of complicated geological conditions, such as high-flow regions and faults, in the reservoir. Thus, for water-flooding to be effective, the well rates of injectors and producers must be selected in an optimal manner.

3.3 Objective Functions

3.3.1 Net Present Value (NPV)

The net present value of a series of cash flows of a project is defined as the aggregate of the present values of individual cash flows which are classified into expenditures and revenues (Khan and Jain 1999). In other words, the net present value can be defined as a combination of capital expenditures, recurrent expenditures and revenues. The capital costs are the major expenses of the project usually incurred at the beginning of the project. These consist mainly drilling, completing and facilities cost. While the recurrent expenditure includes water injection cost, produced water treatment cost and operating cost that involves human resources and well remediation. Revenues are mainly in the form of sales of crude oil and natural gas. Thus the net present value of the waterflooding project can be calculated as (Onwunalu and Durlofsky 2010):

$$NPV = \sum_{n=1}^{N} \frac{CF_n}{(1+r)^n} - C_{cap} \tag{3.1}$$

where

$$C_{cap} = C_{facility} + N_{prod} C_{prod} + N_{inj} C_{inj} , \tag{3.2}$$

$$CF_n = R_n - E_n , \tag{3.3}$$

and

$$R_n = P_n^o Q_n^{o,prod}, \tag{3.4}$$

$$E_n = C_n^{w,prod} Q_n^{w,prod} + C_n^{w,inj} Q_n^{w,inj} + C_{op,n} \tag{3.5}$$

The success of any project is based on its net present value. For this research, NPV is an economic indicator for the field development. It is therefore required to optimize the parameters based on the NPV calculations. When a minimization algorithm is used, the objective function should be (–NPV).

3.3.2 Voidage Replacement Ratio (VRR)

The pressure changing within the reservoir and its environments due to reservoir depletion activities has a considerable environmental impact. One way of observing reservoir pressure balance is the use of the voidage replacement ratio (VRR) which is the ratio of total volume of fluids injected to the volume of fluids produced (Clark and Ludolph 2003). An imbalance between the produced and injected volumes causes an imbalance in reservoir pressure which leads to damage in the environmental system. To avoid this problem, it is necessary to maintain the VRR close to unity. In other words, it is necessary to minimize |VRR – 1|. This absolute value is called the voidage imbalance ratio (Awotunde and Sibaweihi 2014). This VIR has different uses; it can be used as a measure of reservoir energy changes, waterflood performance and for reservoir surveillance. For a waterflood project the yearly cumulative VRR is defined mathematically as:

$$VRR_n = \frac{B_{w,n} Q_n^{w,inj}}{B_{w,n} Q_n^{w,prod} + B_{o,n} Q_n^{o,prod} + B_{g,n} Q_n^{o,prod} \left(GOR_n - R_{so,n} \right)} \tag{3.6}$$

and the VIR can be declared as:

$$VIR_n = \left| VRR_n - 1 \right| \tag{3.7}$$

3.4 Multiobjective Optimization

The basics of multiple objectives optimization are distinct from that in an optimization using single objective. The major intention in the latter is to detect the global optimum solution, which gives the optimum fitness value. Whilst in the former, there are numerous objective functions which are conflicting to each other; each of which may have its own optimum solution, so, there is enough divergence in the optimum solutions conformable to distinct objectives.

The optimization with so discordant objective functions generates a group of optimum solutions in lieu of one global optimum solution; because no solution can be deemed to be better than any other with respect to all objective functions.

Generally, a multiple-objectives optimization problem includes a number of objective functions to be optimized together with a number of equality and inequality constraints which can be formulated as:

Minimizing $f_i\ (x),\ i = 1,\ 2 \ldots\ N_{obj}$, subject to the constraints $\begin{cases} g_i(x) = 0, j = 1, \ldots, M \\ h_k(x) \leq 0, k = 1, \ldots, K \end{cases}$

where 'f_i' is the i^{th} objective function, 'N_{obj}' is the number of objective functions, and 'x' is a solution vector.

Two general approaches have been proposed to address multiobjective optimization problems. One is so called the aggregating techniques, for instance, the weighted sum and the ε-constraint procedures. In the former mode, all objective functions are merged to behave as one objective by scalarizing and pre-multiplying each objective function with scaling and weight factors. This can be formulated as:

$$\text{Min} \sum_{i=1}^{N_{obj}} w_i f_i(x) c_i$$

where *'w_i'* ≥ 0 represent the weighting coefficients which exemplifying the relative importance of the objectives *'f_i (x)'*, and *'c_i'* is a constant multiplier that will scale properly the objectives.

The "ε-constraint" technique is predicated on minimizing only the most favored objective function and taking the remaining objective functions as constraints limit by some permissible levels *'ε_i'*.

Obviously, these aggregating methods can result in only one global solution and require enough prior knowledge about the problem to determine the proper weights or the most preferred objective function, which is not obtainable in most optimization problems such as our case.

The second technique to handle the multiobjective optimization problems is to define the Pareto frontier which includes a collection of optimum solutions. This approach depends on the conjunction between Pareto dominance and evolutionary algorithms. Recently, developments and advancements in population-based algorithms have enhanced the popularity of this method because these algorithms have the merit of estimating many solutions in each iteration which ensure good flexibility for the decision maker especially in which a prior knowledge is not obtainable like in most multiobjective problems.

3.5 Pareto Solution

In multiple objectives optimization problems, any two individuals *'x^1'* and *'x^2'* have one of two possibilities: one dominates the other or non dominates the other. For instance, in the minimization, an individual *'x^1'* dominates *'x^2'* if both following terms are satisfied:

$$f_i\left(x^1\right) \leq f_i\left(x^2\right) \quad \text{for} \quad \forall\, i \in \left\{1, \cdots, N_{obj}\right\} \text{ and } f_j\left(x^1\right) < f_j\left(x^2\right) \quad \text{for} \quad \exists\, j \in \left\{1, \cdots, N_{obj}\right\}$$

When any term is infringed, the individual *'x^1'* does not dominate the individual *'x^2'*. The nondominated solutions are the solutions which are dominating the others in the search space. These nondominated solutions are recognized as Pareto optimum solutions and originate the Pareto optimal front (set) (Abido 2006).

Figure 3.1 shows an example of the Pareto dominance concept. In this example, six solutions have been generated. For instance, if we compare solutions *'1'* and *'2'*, we will find that solution *'1'* is better for a minimization problem. This means that solution *'1'* dominates solution *'2'*. Likewise solution *'2'* dominates *'3'*. Correspondingly solution *'4'* dominates solution *'5'* however they are equal for objective 2.

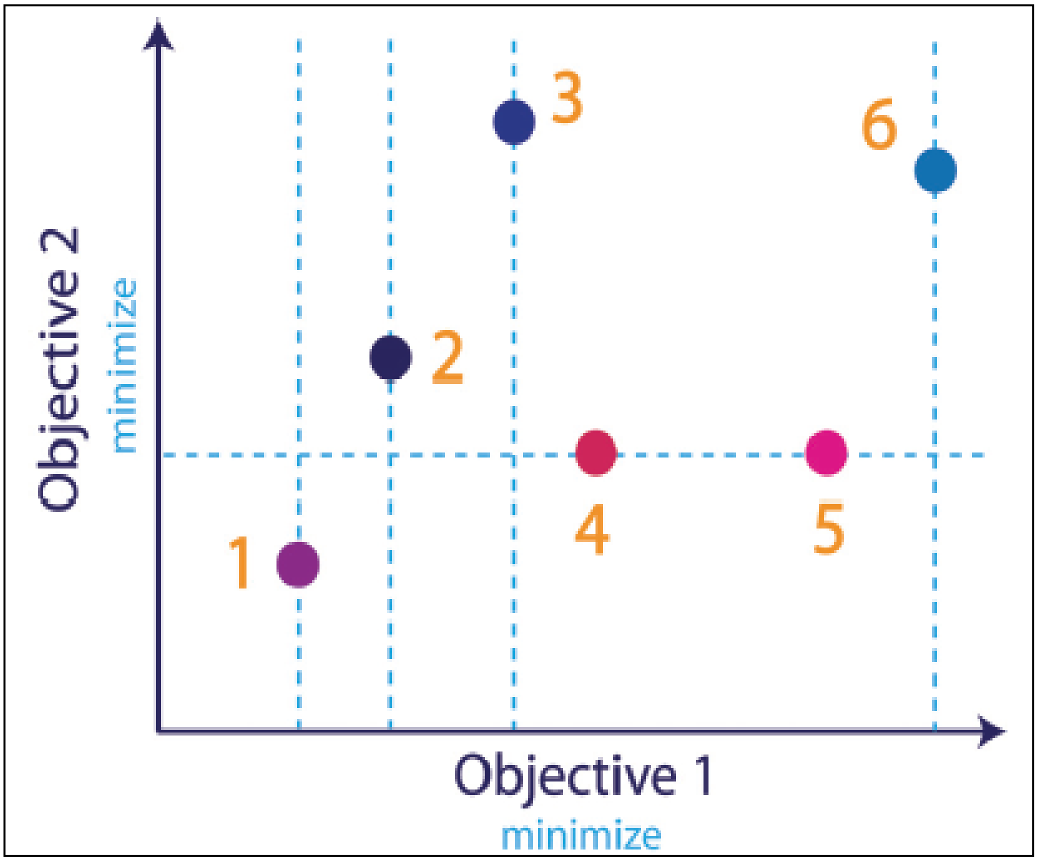

Figure 3.1: An example of multiobjective optimization problem (Hajizadeh et al 2011)

Ordinarily, the two primary aims of a multiple objectives optimization algorithm are to conduct the search in the direction of the optimum Pareto region and to preserve the population variety in the Pareto optimum set (Pareto frontier) in order to prevent premature convergence. The first goal is a normal goal of all optimization algorithms, while the other goal is singular to multiple objectives optimization. Since no one solution in the Pareto frontier can be considered as better than others, what an algorithm can do best is to discover as many different optimum solutions as possible in this frontier. In order to achieve these goals, multiobjective algorithms apply Pareto ranking to define the probability of replication of a solution. In Pareto ranking, a set of nondominated solutions is determined, dedicated the highest rank and taken away from further rivalry. This process is done for all solutions in the search space.

In general, the Pareto optimal front may include a huge number of individuals. Thus, the nondominated individuals in this set should be reduced to manageable size to help the decision maker in selection. In order to shrink the Pareto set, a clustering algorithm can be applied, in which neighboring clusters are merged until obtaining the adequate size of the set. It can be characterized as: given a set P which its size transcends the maximum permissible size N, it is required to shape a subset P^* with the size N. The algorithm for clustering can be explained in the following procedures (Morse 1980):

1. Initialize cluster set C; each individual $i \in P$ constitutes a different cluster.
2. If number of clusters $\leq N$, then go to Step 5, else go to Step 3.
3. Compute the distance of all possible pairs of clusters. The distance d_c of two clusters c_1 and $c_2 \in C$ is given as the average distance between pairs of individuals across the two clusters

$$d_c = \frac{1}{n_1 n_2} \sum_{i_1 \in c_1, i_2 \in c_2} d\left(i_1, i_2\right) \tag{3.8}$$

where n_1 and n_2 are the number of individuals in the clusters c_1 and c_2 respectively. The function d reflects the distance in the objective space between individuals i_1 and i_2.

4. Define two clusters with minimal distance d_c. Combine these clusters into a larger one. Go to Step 2.
5. Determine the centroid of each cluster. Select the nearest individual in this cluster to the centroid as a representative individual and eliminate all other individuals from the cluster.
6. Calculate the reduced nondominated set P^* by uniting the representatives of the clusters.

3.6 Differential Evolution

Recently, evolutionary algorithms are becoming effective tools to solve intricate problems in optimization, including single objective and multiobjective optimization problems. Differential evolution (DE) was introduced as one of the evolutionary algorithms which are population-based techniques. It was proposed during 1994 and 1996, by Kenneth Price and Rainer Storn. The former was the person who started to work on 'Chebyshev Polynomial Fitting Problem' by solving it using vector differences for vector population perturbation. Their efforts ended up in the formulation of a technique known as Differential Evolution. Since then, many researchers got attracted to this algorithm and it has been widely applied in solving different engineering problems, e.g.

non-linear programming, non-differentiable problems, function minimization and complex simulations. (Storn 1995, Storn and Price 1995, Storn 1996, Storn and Price 1996, Lampinen and Zelinka 1999, Lampinen 2001, Karaboga and Okdem, 2003, Coello et al. 2007).

The DE, as in any evolutionary technique, generally performs three steps: initialization, creating new trial generation and selection.

3.6.1 Initialization

As a preparation for the optimization process, the following requirements should be specified:

- Problem dimensions '*D*' should be defined at the start of the solution. It depends upon the number of the design parameters. The individual range of the parameters is very important as the optimization technique will search for the optimum solution within this prescribed range.
- The constraints used to guide the global optimization.
- Size of population 'N_p'
- Number of iterations '*i*'
- Crossover factor '*CR*'
- Mutation factor '*F*'

DE starts with the generation of 'N_p' vectors (candidate solutions or population). Each solution is composed of '*D*' number of control variables (optimized parameters). This can be achieved by randomly specifying values for each parameter 'x_i' within its domain.

$$x_{i,j} = x_{j_{min}} + random\ \#\left(x_{j_{max}} - x_{j_{min}}\right) \tag{3.9}$$

where

i = 1: N_p, *j = 1: D*

3.6.2 Evaluation and Finding the Best Solution

The objective function value for each solution (vector) is evaluated and compared to other solutions to obtain the preferable solution of the generation. The global best solution is stored externally and updated after every generation.

3.6.3 Mutation

Mutation is the first step for generating new solutions. In this operation, a mutant vector is generated for every solution in the initial population using one of the following formulas:

$$V_i^{(G+1)} = X_{r1}^{(G)} + F\left(X_{r2}^{(G)} - X_{r3}^{(G)}\right), \tag{3.10}$$

or

$$V_i^{(G+1)} = X_{best}^{(G)} + F\left(X_{r1}^{(G)} - X_{r2}^{(G)}\right), \tag{3.11}$$

or

$$V_i^{(G+1)} = X_i^{(G)} + F\left(X_{best}^{(G)} - X_i^{(G)}\right) + F\left(X_{r1}^{(G)} - X_{r2}^{(G)}\right), \tag{3.12}$$

or

$$V_i^{(G+1)} = X_{r1}^{(G)} + F\left(X_{r2}^{(G)} - X_{r3}^{(G)}\right) + F\left(X_{r4}^{(G)} - X_{r5}^{(G)}\right) \tag{3.13}$$

where

$X_{r1}^{(G)}, X_{r2}^{(G)}, X_{r3}^{(G)}, X_{r4}^{(G)}, X_{r5}^{(G)}$ are selected as random distinct vectors from the current generation

$X_{best}^{(G)}$: solution achieving best value

F: mutation constant having a range of [0,2], which controls the speed of convergence.

3.6.4 Crossover

Crossover operation is employed to further perturb the generated solutions and enhance the diversity. In crossover operation, the initial vector (parent) and its corresponding mutant vector (generated in mutation) in the original population are reproduced to a new vector named as trial vector. This is done by considering a certain crossover factor *CR* having a range of [0,1] defined by the user. A random number in the range of [0,1] is generated for each parameter in the solution and compared with the *CR*. If this generated number is less than or equal to *CR*, then the parameter for this trial vector is selected from mutant vector otherwise it will be selected from parent vector. In case, *CR* is set equal to zero, then all the parameters for trail vector are taken from initial vector except one parameter randomly selected from the mutant vector. However, if *CR* is defined as one, then all the parameters for trail vector are taken from mutant vector except one parameter randomly selected from the parent vector.

CR plays a significant role in controlling the smoothness of the convergence. Small value of *CR* causes the trial solutions to have the characteristics of their parent vectors and hence, slow in convergence.

3.6.5 Selection

Selection is the last step for generation of new population. In selection process, the objective function values are evaluated for each entry of trial vector and then compared with the corresponding value for the objective function of the old generation. The solutions having the best objective function value are progressed to new generation.

3.6.6 Stopping Criteria

After every generation, DE calculates the global best solution and updates it. Usually maximum number of generation is set to be as the stopping criteria. However, the user can examine the change in global best solution values and if the change is within the tolerance limit, then it can be selected as stopping criteria.

All these steps for Differential Evolution algorithm are shown in Figure 3.2.

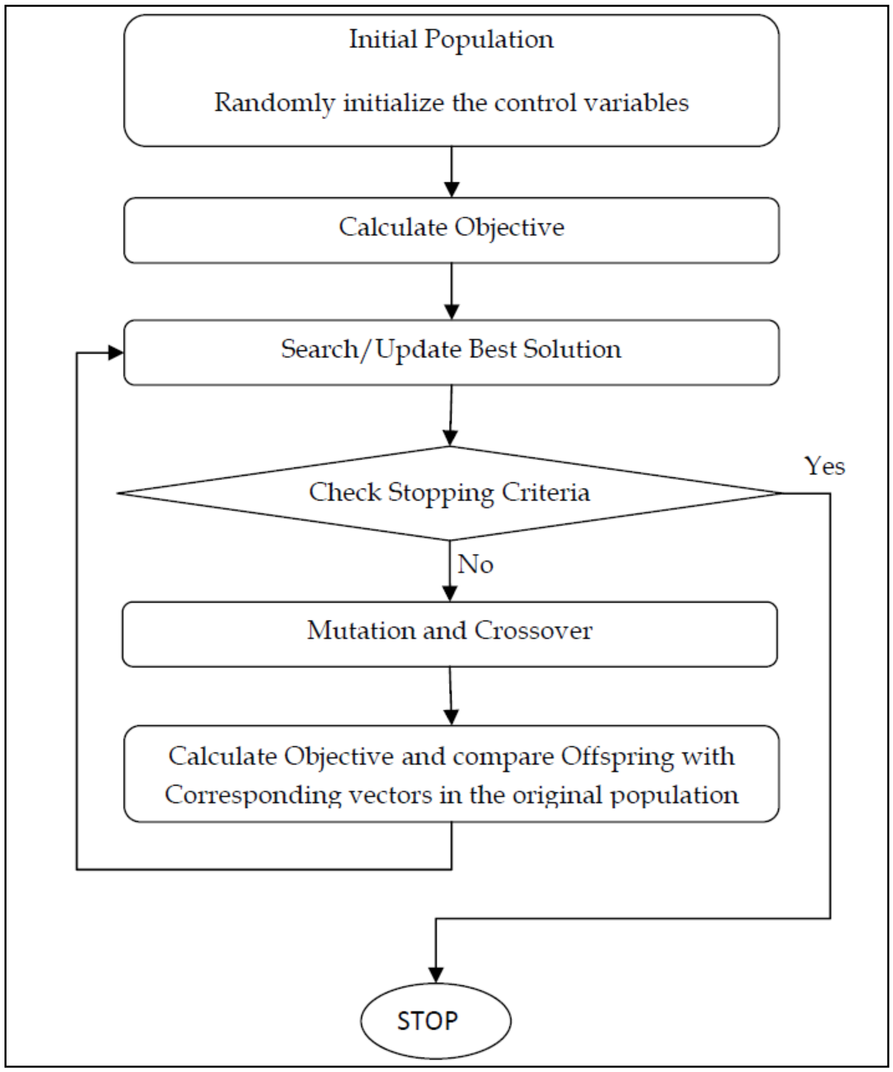

Figure 3.2: Flow chart of DE for single objective optimization

3.7 Multiobjective Differential Evolution

The original differential evolution algorithm that is used for single-objective optimization can be expanded to be used for the multiobjective problems by combining the concept of Pareto optimal with the mutation operator. Therefore, this technique includes three main processes; those are mutation, Pareto-based evaluation and selection (Xue et al 2003).

3.7.1 Mutation Operator

In multiobjective Pareto-based techniques, the target is to find the optimal Pareto solutions instead of one solution. With a view to imitate the mutation operator in single objective differential evolution, two vectors should be defined; perturbation and differential vectors. Figure 3.3 shows an illustrative example of mutation operation. In this example, to mutate an individual 'P_i', we have to check whether this individual is dominated or not. If it's a dominated, a set of nondominated individuals 'D_i' and the best randomly selected solution 'P_{best}' can be defined and the differential vector is specified as the vector between P_i and P_{best}. But if P_i is initially nondominated (e.g. P_j), the differential vector will be zero and P_{best} becomes the individual itself. In both cases, the perturbation vector is specified by randomly selected individual couples from the parent population. After determining the perturbation and differential vectors, the mutation can be formed as:

$$P_i' = \begin{cases} P_i + F.\sum_{k=1}^{K}\left(P_{i_a^k} - P_{i_b^k}\right), if \;\; P_i \; is \; nondominated \\ \gamma.P_{best} + (1-\gamma)P_i + F.\sum_{k=1}^{K}\left(P_{i_a^k} - P_{i_b^k}\right), otherwise \end{cases} \tag{3.14}$$

$P_{i_a^k}$, $P_{i_b^k}$ are randomly chosen distinct individuals and $\gamma \in [0,1]$ is the operator glutton.

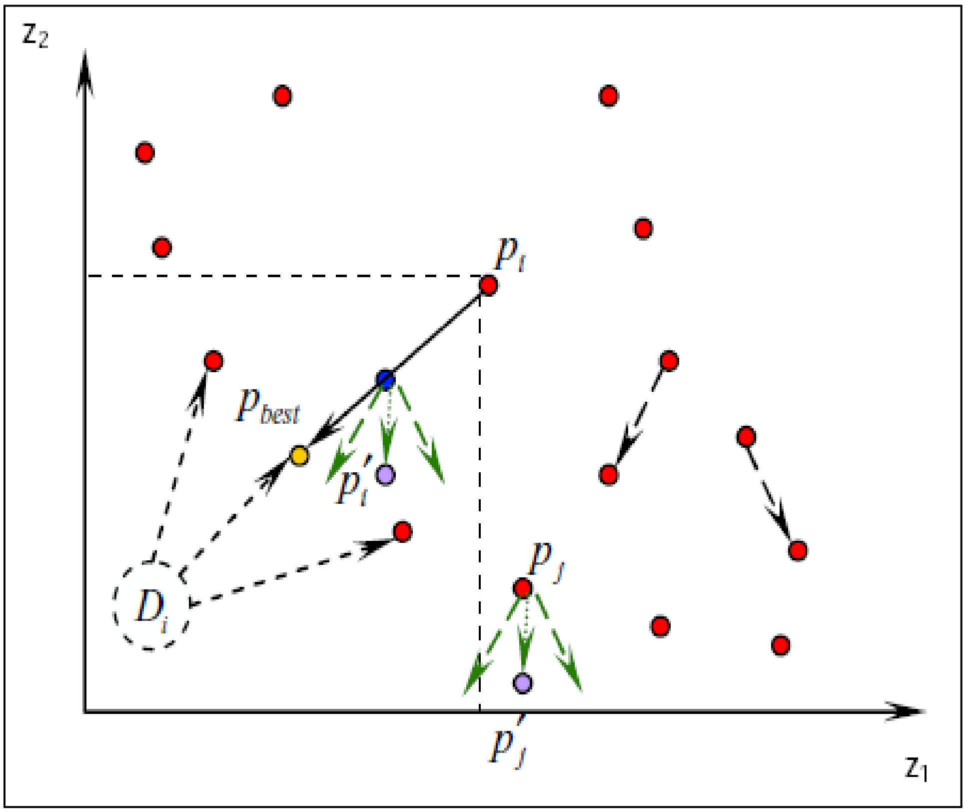

Figure 3.3: An illustrative example of mutation operation in DE for multiobjective optimization (Xue et al 2003)

3.7.2 Pareto-Based Evaluation

The Pareto ranking can be applied to evaluate all individuals in the entire search space. In this assignment as shown in Figure 3.4, the nondominated individuals, which their fitness values are the highest, are specified as rank 1 and extracted from the competition. A new group of nondominated individuals those have the next highest fitness values in the remainder of the population are assigned as rank 2, and so on till all individuals in the search space are ranked.

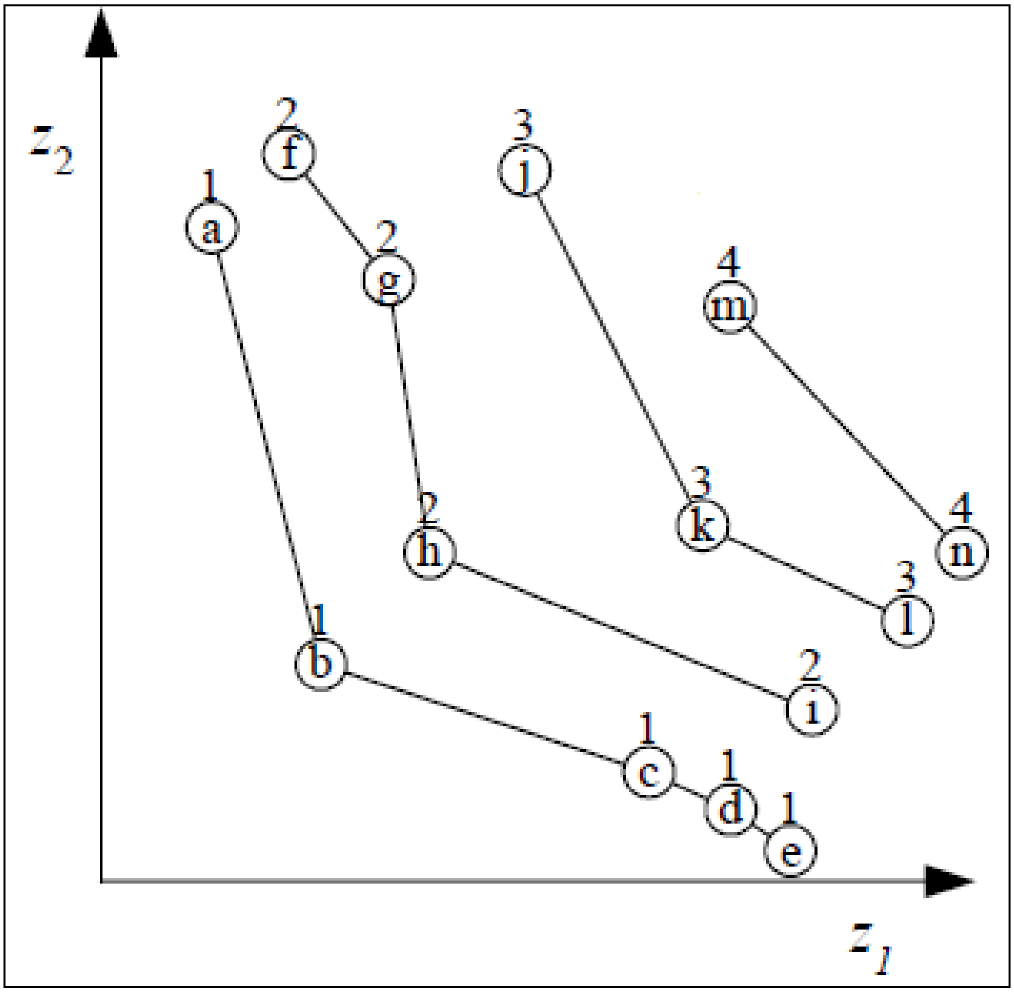

Figure 3.4: Concept of Pareto ranking

3.7.3 Selection operator

In selection process, the parent and offspring individuals are vied for proceeding to the new generation. The operation is done by comparing the individuals' ranks; as a result, the highest ranked individuals are preceded. If the ranks are equalized, the crowd distance can be used. But to block the premature convergence by proceeding similar individuals, another parameter 'σ_{crowd}' should be defined which specifying how close the individual is to its surrounding individuals in objective space so as to reduce its fitness to a very tiny value.

Figure 3.5 shows the flow chart for the Pareto-based multiobjective differential evolution algorithm.

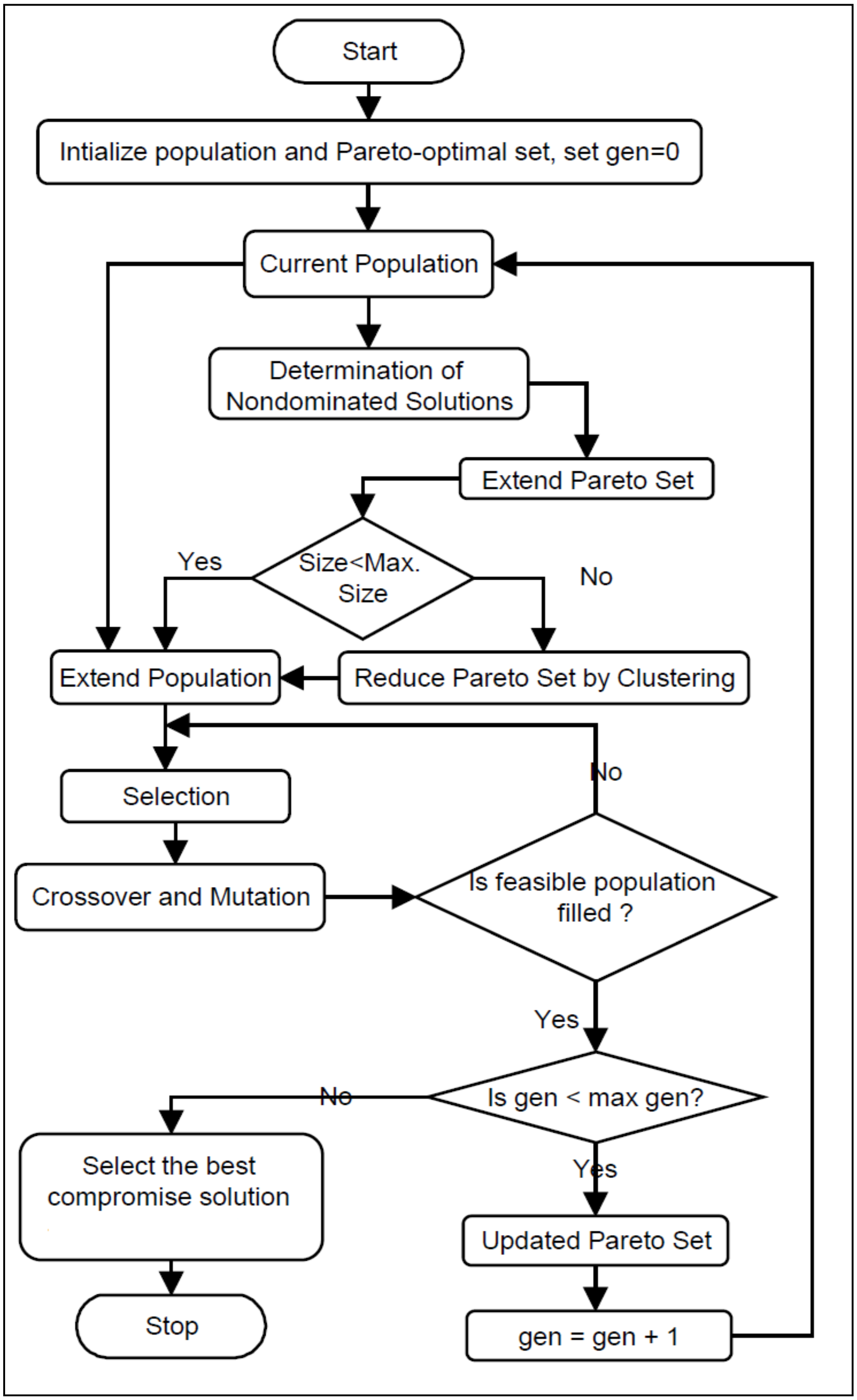

Figure 3.5: Flow chart for Pareto-based multiobjective DE algorithm

CHAPTER 4

WORK DESCRIPTION

4.1 Sample Illustration

Two sample optimization problems were used to show the usefulness of the Pareto-based multiobjective optimization approach. Each of these problems was solved for three scenarios; in the first scenario, only the best (x,y)-configuration of wells was determined while in the second, the optimum wells operating rates were defined and lastly, both well placement and rate were simultaneously optimized. In all scenarios, the NPV and the VRR were synchronously optimized. But before that a confirmation test is done using one reservoir to examine the importance of considering multiobjective optimization. In which, three cases are studied by optimizing a single objective function; only the NPV and only the VRR then optimizing a combination of them using a weighted sum technique. Table 4.1 shows the values of variables used in calculating the NPV. The cost of each well is assumed to be $\$2.5\times10^6$. The oil price, the costs of water injection and disposal, and the operating cost are assumed to be constant throughout the period of operation.

Table 4.1: Variables used in calculating the NPV

Variable	Value	Unit
$C_{facility}$	50×10^6	$
C_{prod}	2.5×10^6	$
C_{inj}	2.5×10^6	$
P^o_n	105	$/bbl
$C_n^{w, prod}$	5	$/bbl
$C_n^{w, inj}$	10	$/bbl
$C_{op, n}$	8	$/bbl
r	10	%

To solve the optimization problems, multiobjective differential evolution algorithm with Pareto ranking is employed as an optimizer.

The population size 'N_p' of the algorithm is obtained using Eq. (4.1). In the algorithm, the mutation factor 'F' is set at 0.90 and the crossover factor 'CR' is chosen to be 0.90 and the maximum number of generations is set to 300 for both samples.

$$N_p = 4 + floor(3 * \log(N)) \tag{4.1}$$

where 'N' is the problem dimensions and '*floor ( )*' is a function that rounds a number to its nearest integer towards minus infinity.

4.2 Reservoir Models

This research used two synthetic reservoirs; channel reservoir and a reservoir with fully distributed permeability field to verify the success of the algorithm. The former is discretized into 75×75×2 gridblocks, each block is of size 200*ft*×200*ft*×100*ft*, whereas the latter is discretized into 64×64×3 gridblocks each block is of size 200*ft*×200*ft*×100*ft*.

Both reservoirs contain undersaturated oil and the fluids are produced at pressures above the bubble point pressure of 1900 *psig*. Eighteen producers and twelve injectors are to be placed in each reservoir; all these wells are drilled at the beginning of the project. The time for running and calculations is twelve years.

Values of relative permeability for water and oil and the PVT properties of undersaturated oil are presented on Tables 4.2 and 4.3 and shown in Figures 4.1 and 4.2 respectively. Both reservoirs have different heterogeneity and their permeability distribution is shown in Figures 4.3 to 4.7. The minimum well spacing is set to be 10 acres.

Table 4.2: Relative permeability for water and oil

S_w	K_{rw}	K_{ro}
0.22	0	1
0.3	0.07	0.4
0.4	0.15	0.125
0.5	0.24	0.0649
0.6	0.33	0.0048
0.8	0.65	0
0.9	0.83	0
1	1	0

Table 4.3: PVT properties of undersaturated oil

Pressure	B_o	μ_o
1900	1.285304386	0.713869686
2300	1.27678122	0.891017852
2700	1.269628174	0.988584181
3100	1.26346515	1.045833676
3500	1.25805112	1.082583389
3900	1.253223604	1.109461714
4300	1.248867854	1.132397737
4700	1.244899818	1.154772241
5100	1.24125608	1.178522068
5500	1.237887612	1.204738625
5900	1.23475573	1.234006504
6300	1.23182937	1.266601815
6700	1.22908321	1.302611613
7100	1.226496341	1.342007425
7500	1.224051291	1.384691289
7900	1.221733315	1.430524938
8300	1.219529854	1.479348438

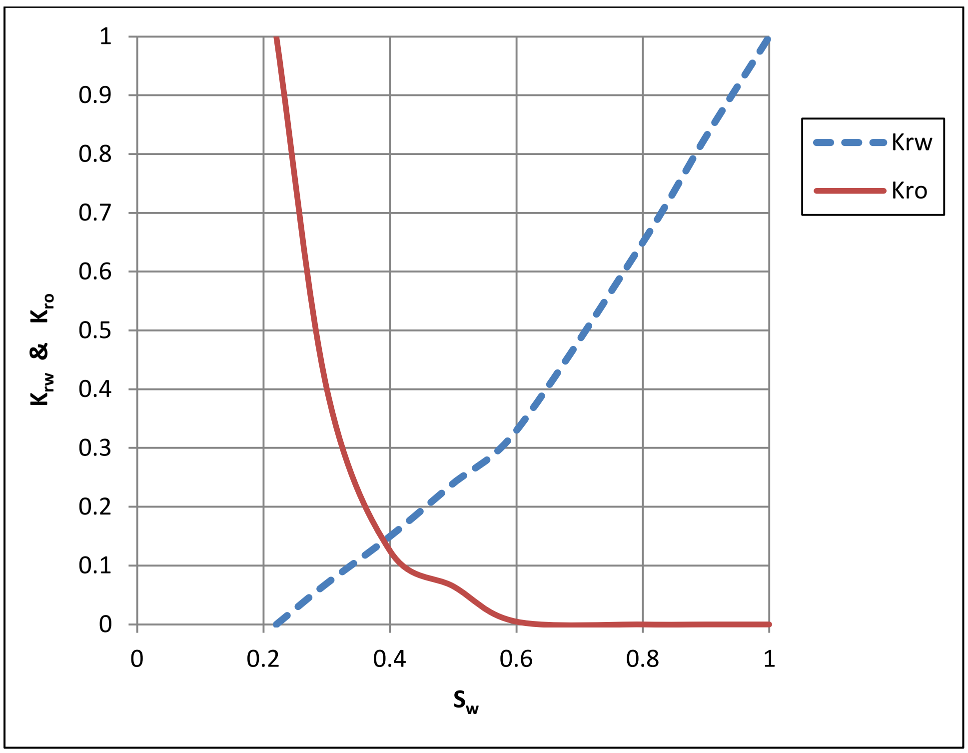

Figure 4.1: Relative permeability for water and oil

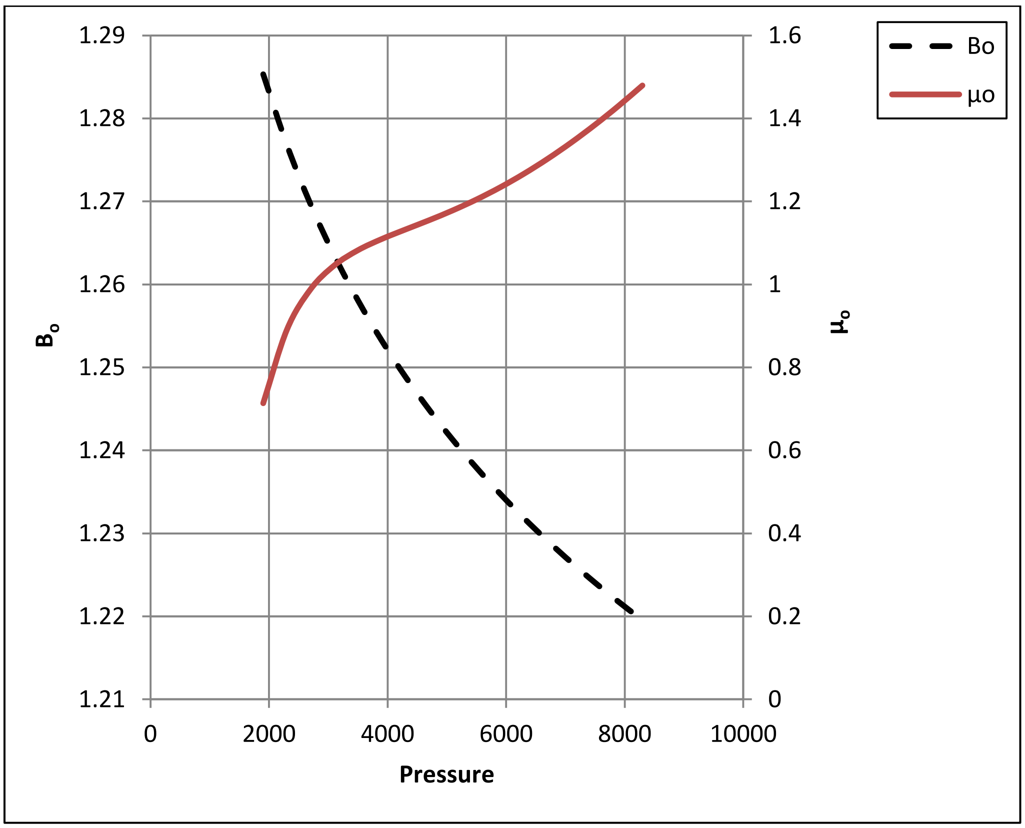

Figure 4.2: PVT properties of undersaturated oil

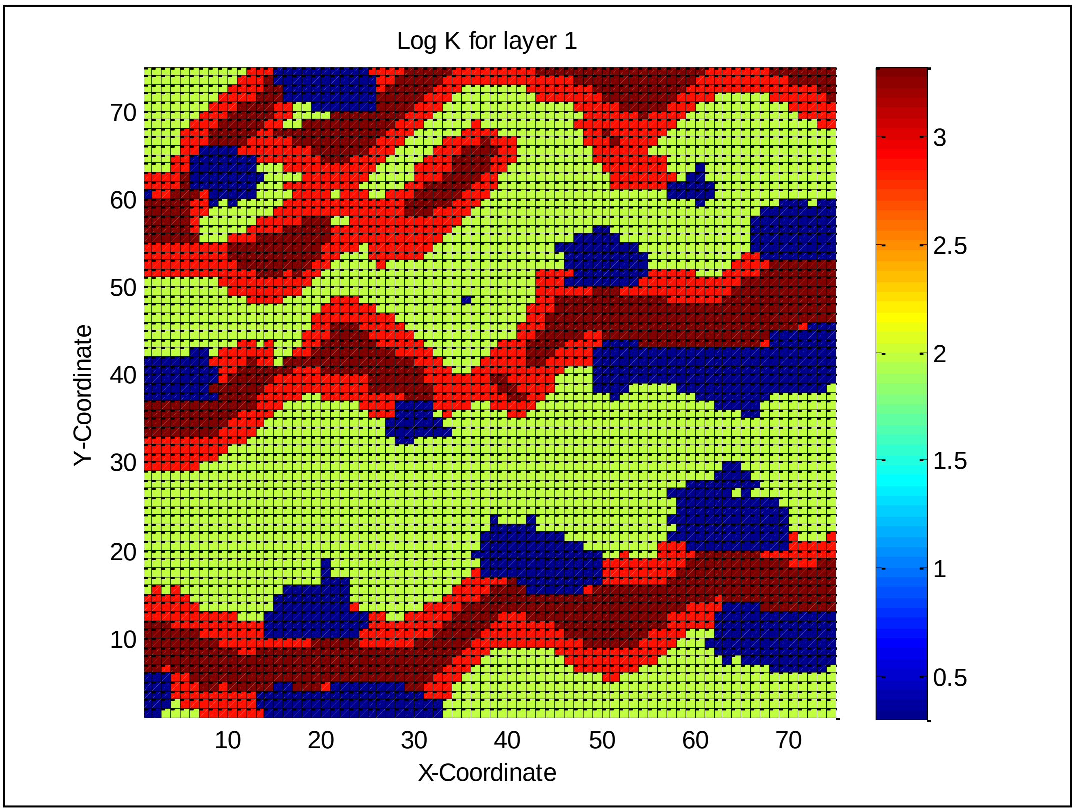

Figure 4.3: Log permeability distribution for layer #1 in channel reservoir

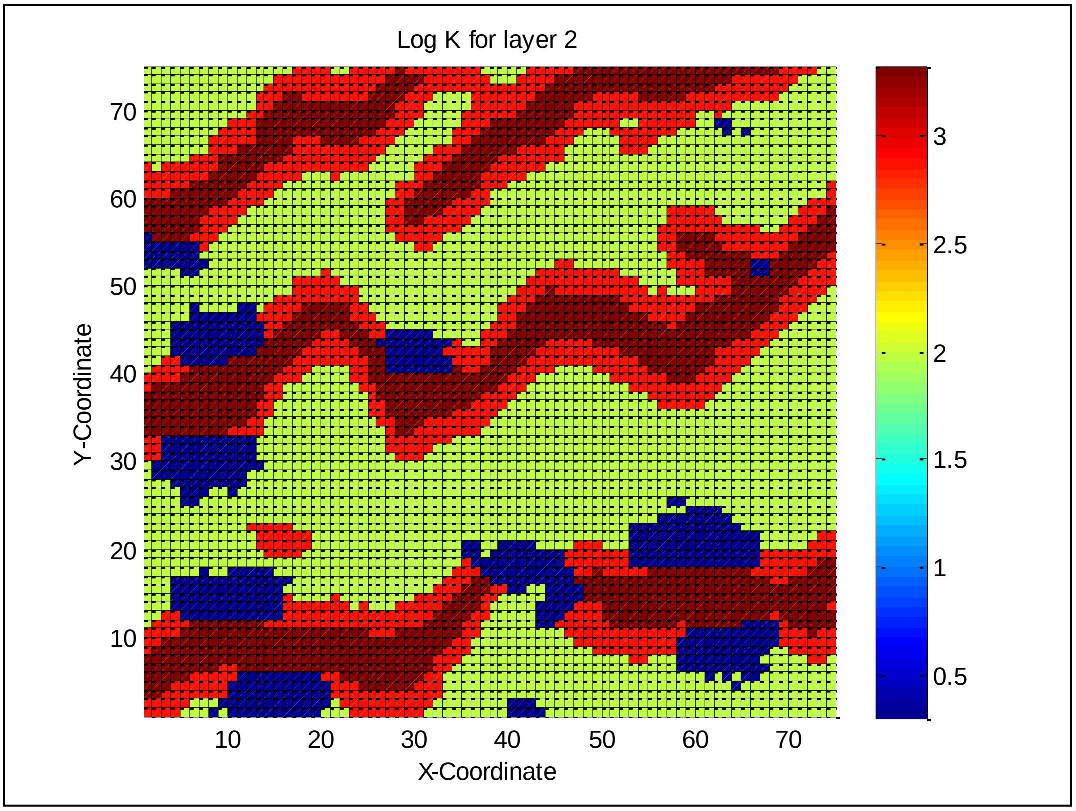

Figure 4.4: Log permeability distribution for layer #2 in channel reservoir

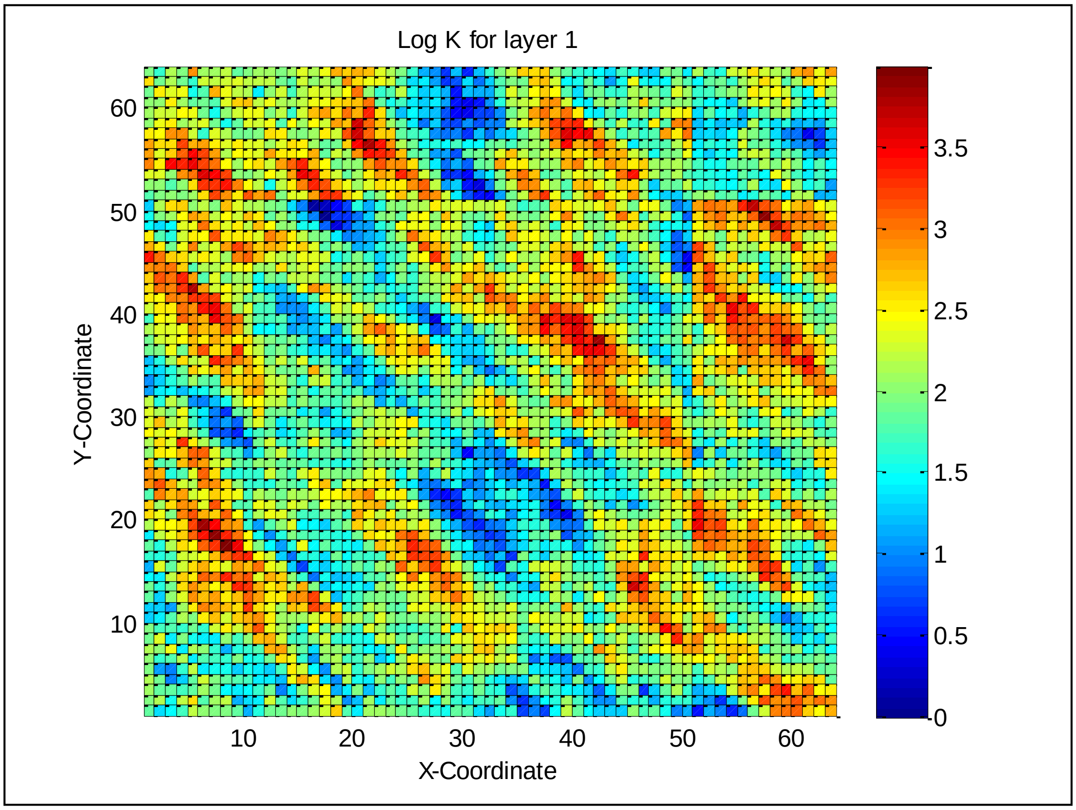

Figure 4.5: Log permeability distribution for layer #1 in distributed permeability reservoir

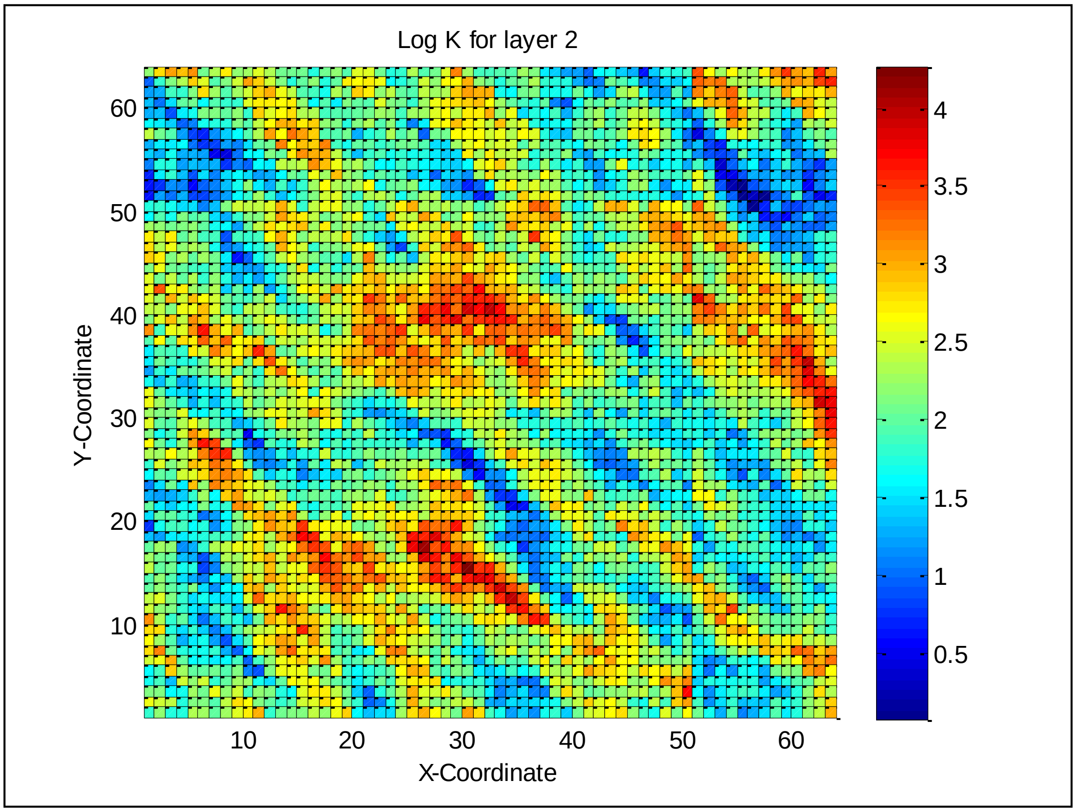

Figure 4.6: Log permeability distribution for layer #2 in distributed permeability reservoir

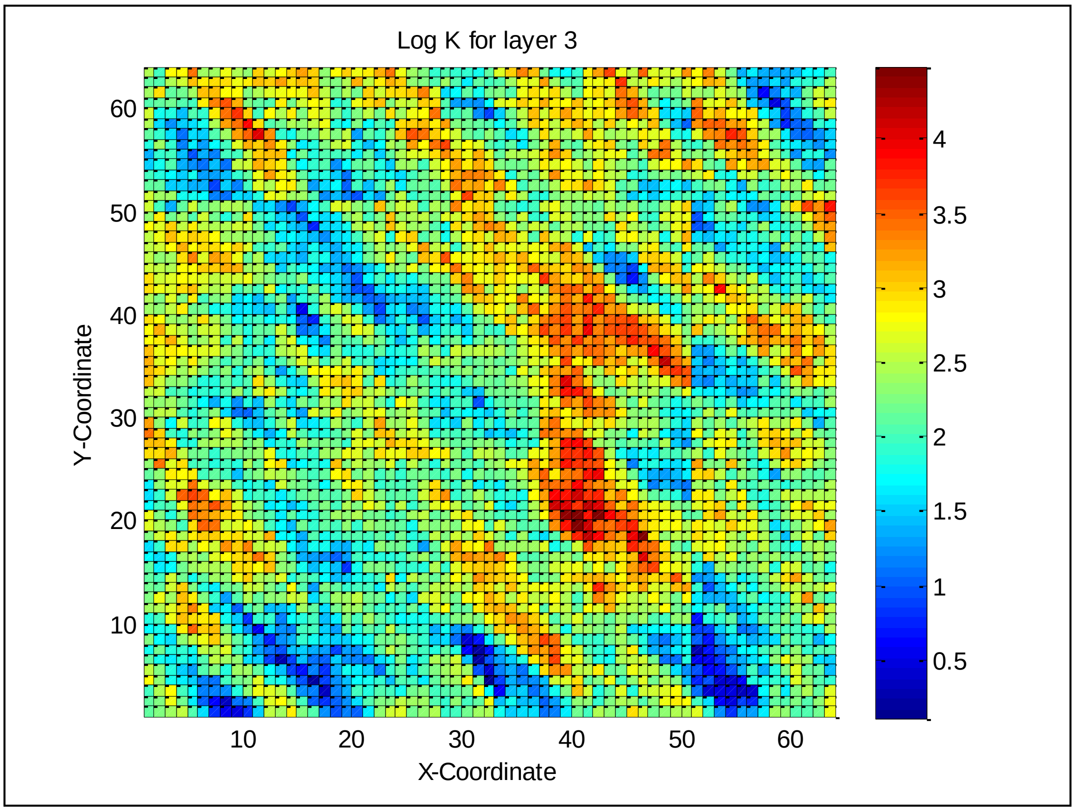

Figure 4.7: Log permeability distribution for layer #3 in distributed permeability reservoir

CHAPTER 5

RESULTS AND DISCUSSIONS

In this chapter, we present the results of four cases (optimizing only NPV, only VIR, a combination of NPV and VIR using weighted sum technique with equal weights, and optimizing both NPV and VIR using Pareto-based technique) under three optimization scenarios. The first scenario involves the determination of optimum well locations only. In the second scenario, optimum well rates were determined. In the third, both optimum well locations and rates were estimated. We define a base case in which the wells were located using Direct-line pattern and the operating rates for producers and injectors were set to be constant at 1500 and 3000 *STB/d* respectively.

5.1 Example 1: Channel Reservoir

Figure 5.1 shows the well configuration in the base case for this channel reservoir.

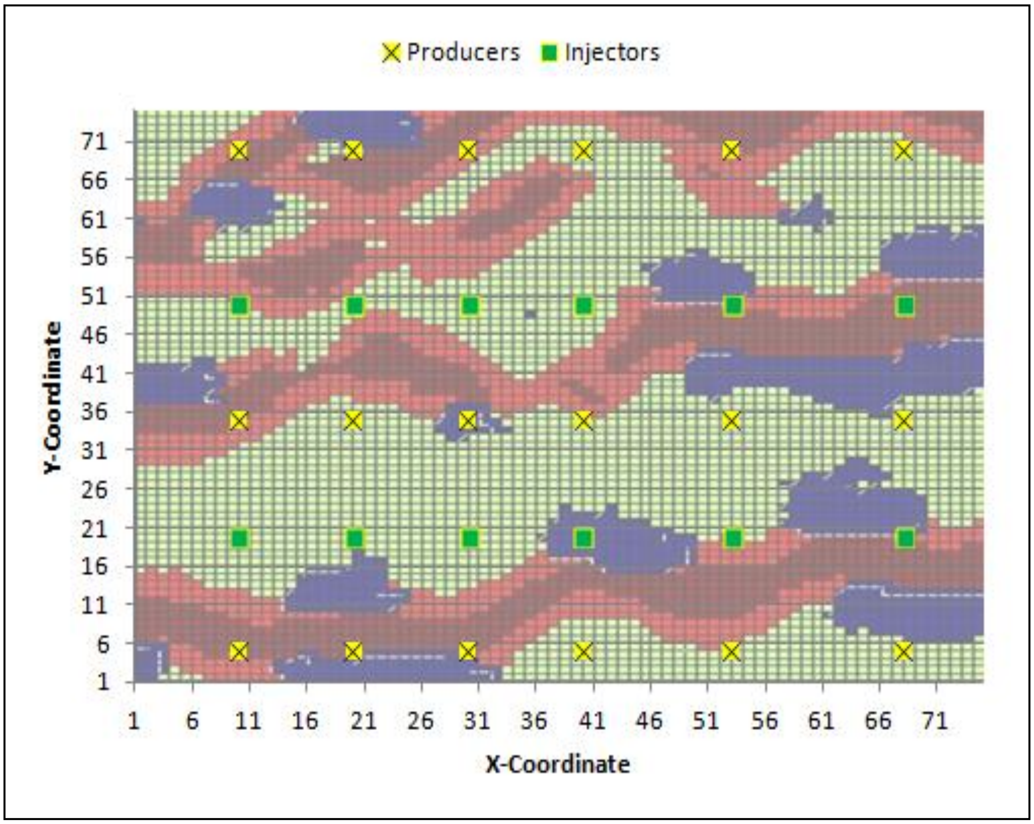

Figure 5.1: Well locations in the base case for Example 1

5.1.1 Scenario 1: Well Placement Optimization

The results of the four cases for this scenario are presented on Table 5.1 and the values are shown in Figure 5.2.

Table 5.1: The NPV and VIR values for base case and the four cases for Example 1, Scenario 1

	NPV $\times 10^9$	**VIR**
Base Case	3.494	0.173
NPV Only	5.676	0.2219
VIR Only	4.187	0.0067
Weighted Sum	5.034	0.0114
Pareto-based (Best NPV)	5.296	0.0123
Pareto-based (Best VIR)	4.912	0.0098

Form Table 5.1 and Figure 5.2, optimizing only NPV gives superior value for NPV but not for VIR. Similarly, optimizing only VIR gives optimum value for VIR with less NPV. In multiobjective optimization, the weighted sum technique generates one solution, when the Pareto-based approach gives different solutions; we presented two of them on Table 5.1 (i.e. solution with the best NPV and the other with the best VIR value).

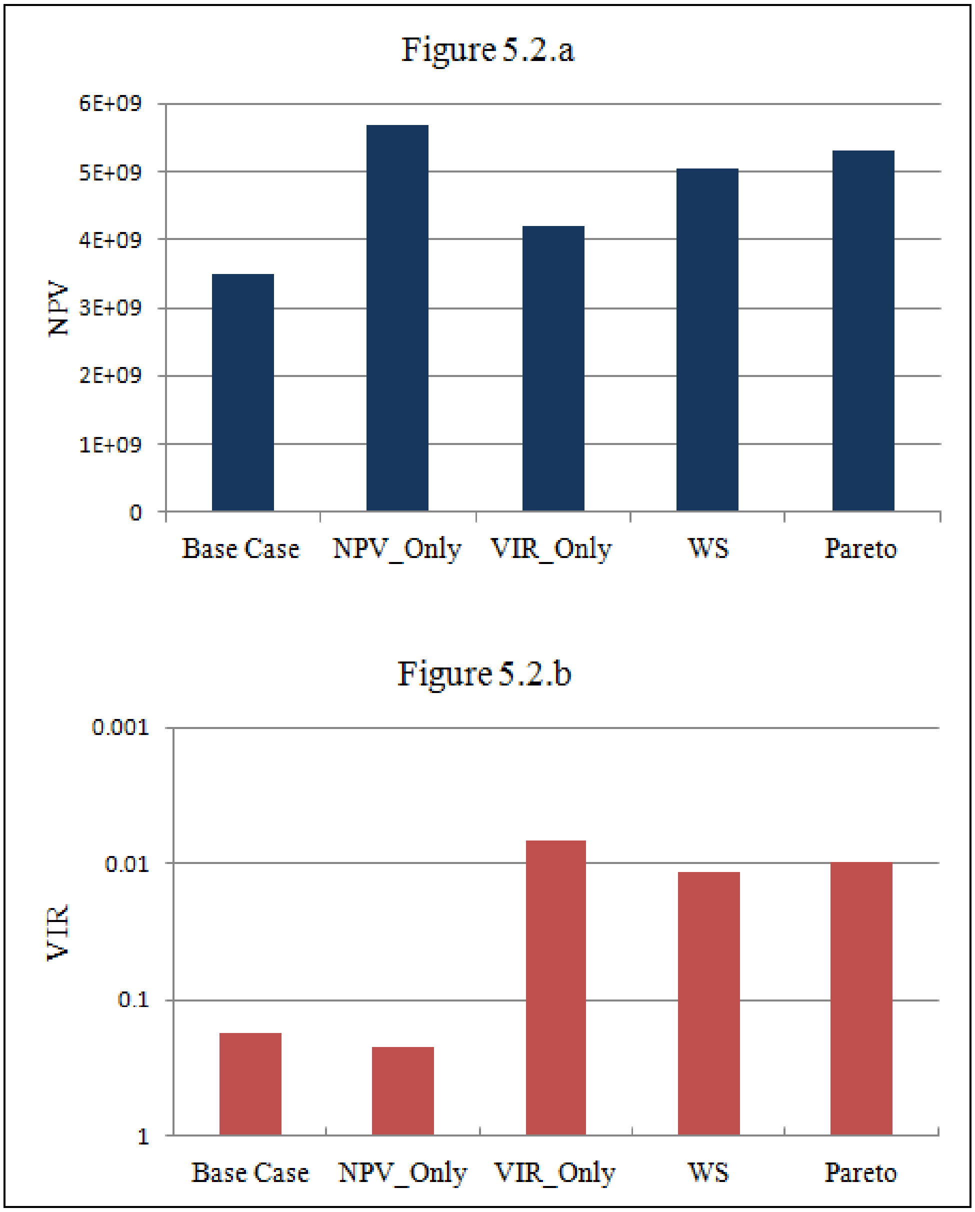

Figure 5.2: The resulted values of a) NPV and b) VIR for base case and the four cases for Example 1, Scenario 1

From these results, considering the environmental effect has an impact on NPV values. So it's important to consider both economical and environmental aspects. Obviously, using Pareto-based approach for multiobjective optimization gives alternative solutions from which the user can choose. In this example, the Pareto-based technique generates a set of three solutions called Pareto optimal set (Pareto Front) as shown in Figure 5.3 and the values are presented on Table 5.2. Therefore, the Pareto-based technique provides different options for the decision makers; all these options are superior in some sense for the investors and environmental agencies, which guarantee the optimality of whatever selection the decision-maker takes.

Table 5.2: The VIR and NPV values from Pareto Front for Example 1, Scenario 1

VIR	**NPV** $\times 10^9$
0.0123	5.296
0.0106	5.266
0.0098	4.912

The first solution on Table 5.2 is considered as the best option for the investors and the corresponding well configurations are shown in Figure 5.4. Meanwhile the last solution is the best one from the environmental regulatory point of view and the corresponding well locations are shown in Figure 5.5. However the difference in VIR values between the best and the worst is not significant and choosing any one of the three solutions may be satisfactory to the regulators in this case. Figure 5.6 shows the well locations corresponding to the median NPV and VIR.

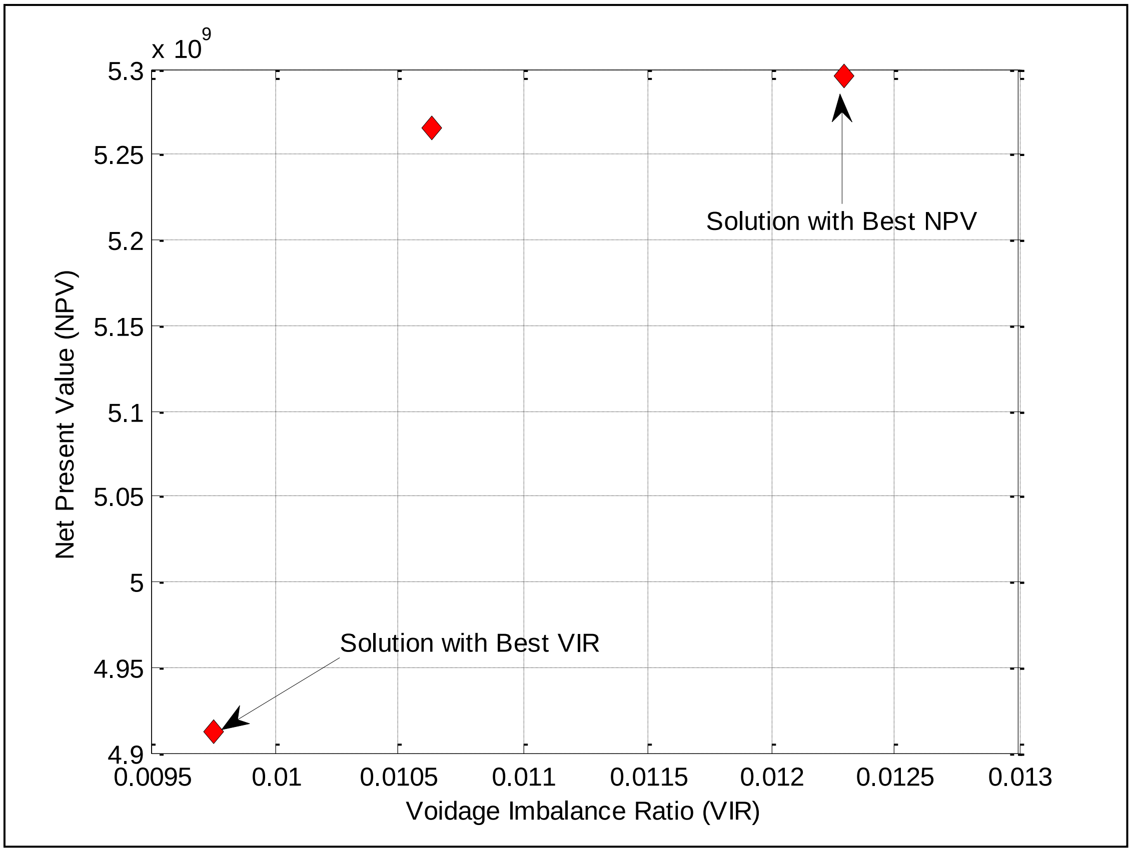

Figure 5.3: The resulted Pareto optimal set for Example 1, Scenario 1

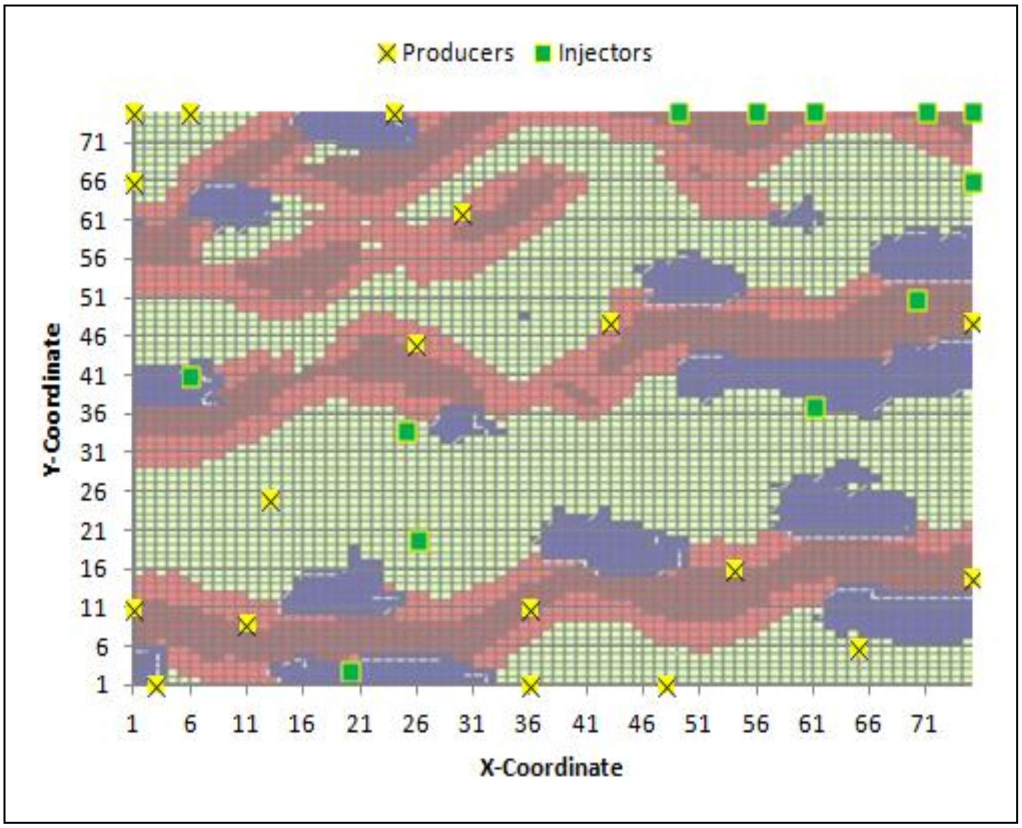

Figure 5.4: Well locations corresponding to the best NPV in the Pareto set for Example 1, Scenario 1

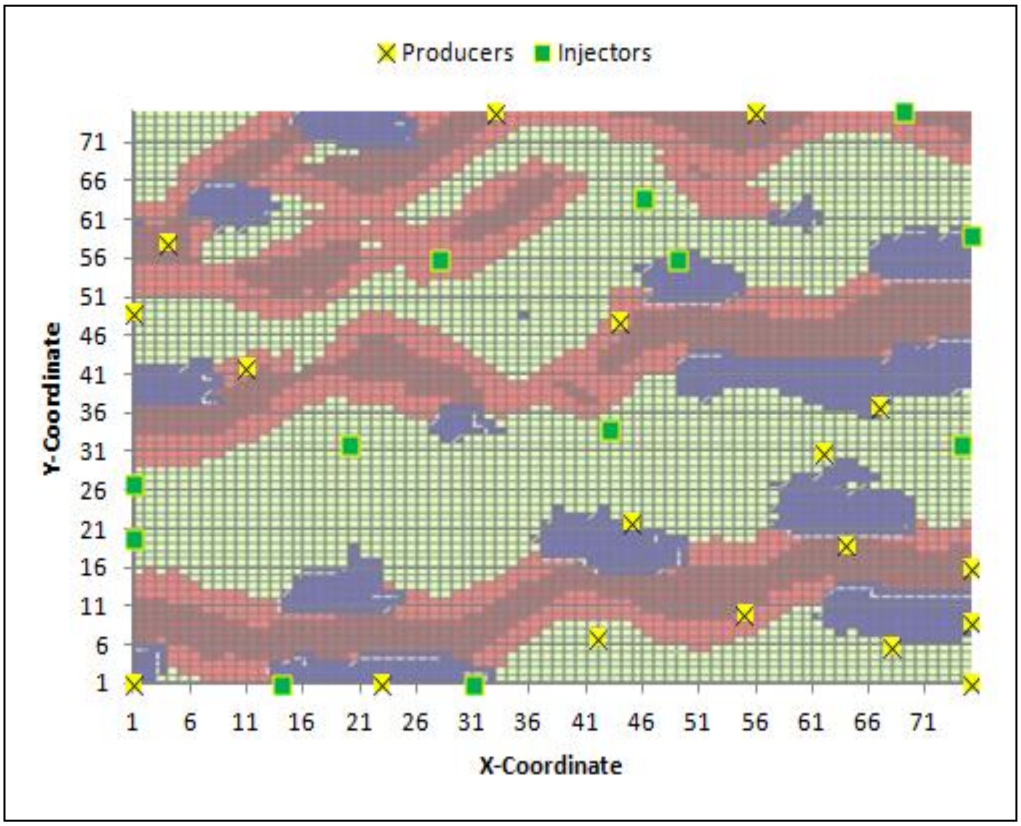

Figure 5.5: Well locations corresponding to the best VIR in the Pareto set for Example 1, Scenario 1

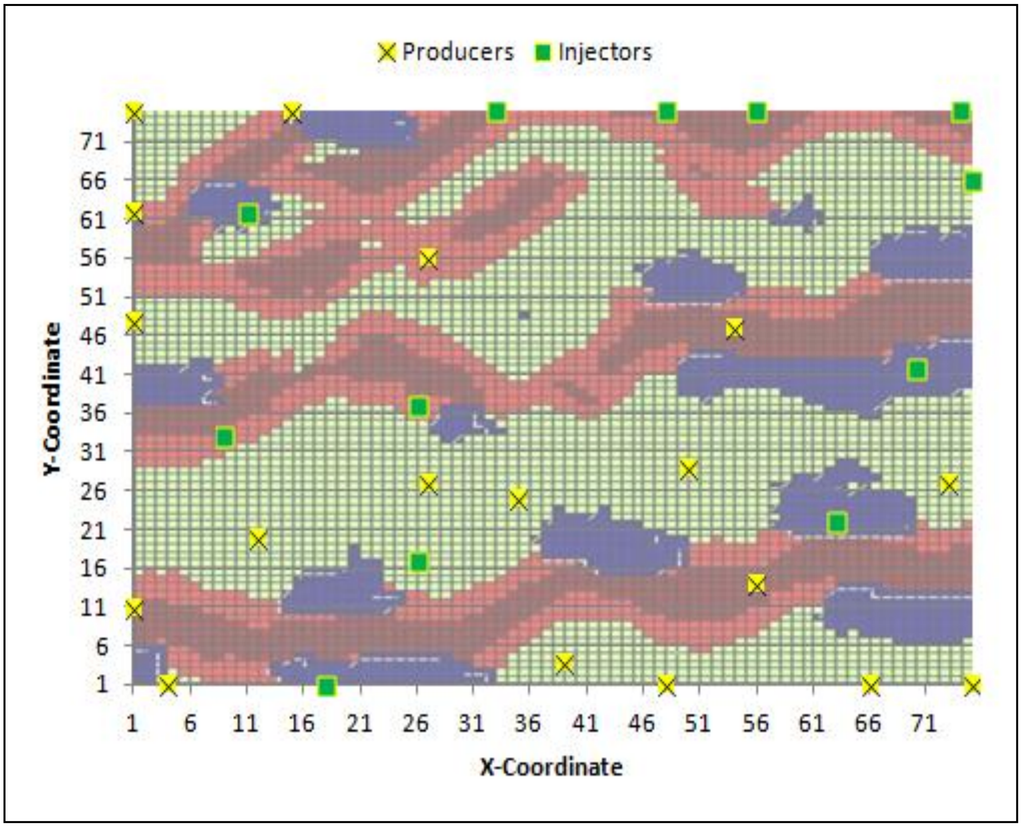

Figure 5.6: Well locations corresponding to the median solution in the Pareto set for Example 1, Scenario 1

5.1.2 Scenario 2: Well Rate Optimization

In this scenario, only the operating rates for producers and injectors were optimized. It was assumed that the locations of the wells were known. The results are presented on Table 5.3.

Table 5.3: The NPV and VIR values for base case and the four cases for Example 1, Scenario 2

	NPV $\times 10^9$	**VIR**
Base Case	3.494	0.173
NPV Only	11.47	0.2437
VIR Only	6.275	0.0136
Weighted Sum	8.636	0.0309
Pareto-based (Best NPV)	9.965	0.1269
Pareto-based (Best VIR)	8.151	0.0278

Figure 5.7 shows the advantage of using the Pareto-based approach. In the Pareto approach, the economic and environmental aspects are considered in multiple optimal options making it more suitable than the weighted sum technique.

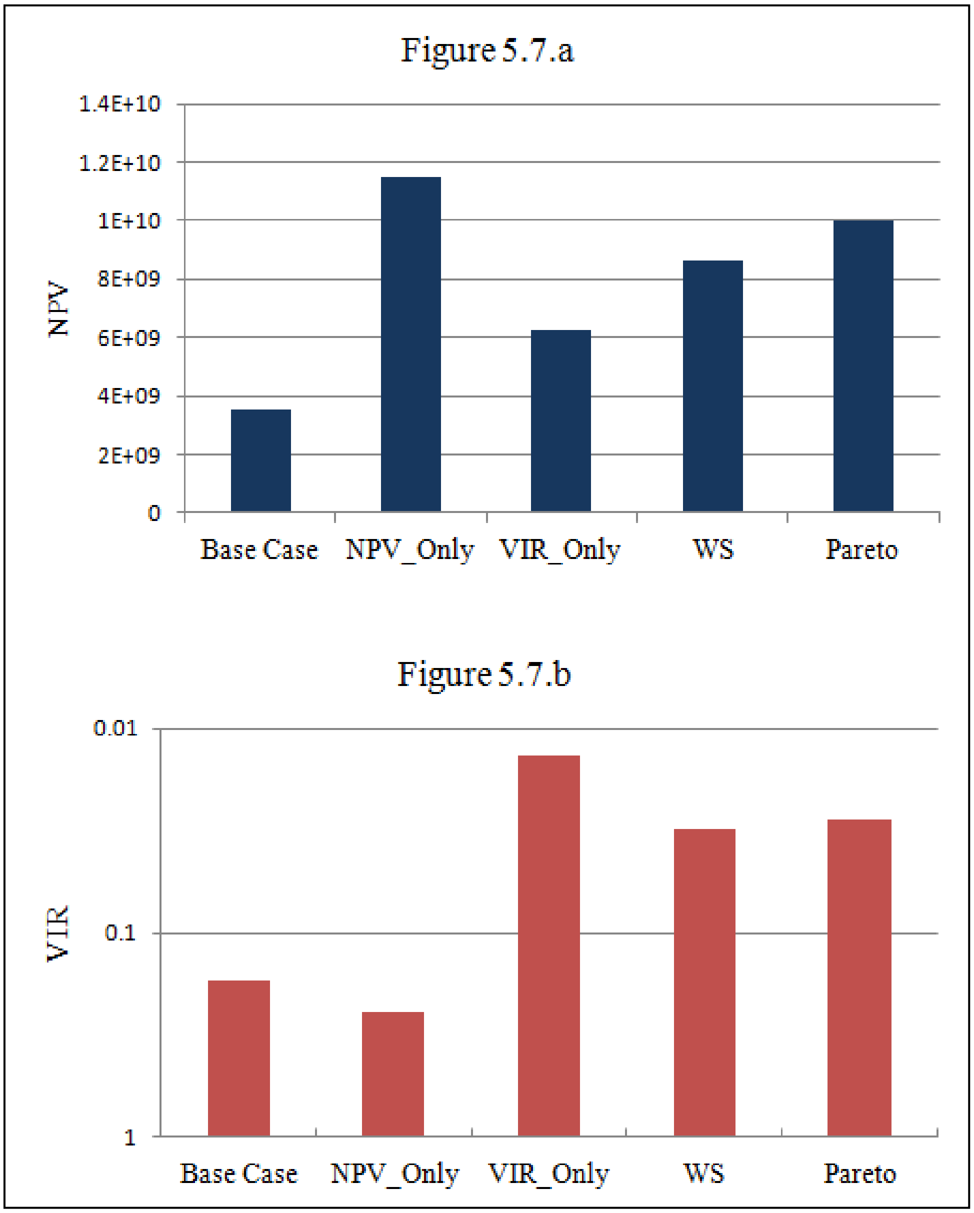

Figure 5.7: The resulted values of a) NPV and b) VIR for base case and the four cases for Example 1, Scenario 2

The Pareto-based approach generated five superior solutions that formed the Pareto front as shown in Figure 5.8. The NPV and VIR values of these solutions are presented on Table 5.4. All solutions are optimal in some sense for both environmental and economical criteria.

Table 5.4: The VIR and NPV values from Pareto Front for Example 1, Scenario 2

VIR	**NPV** $\times 10^9$
0.1269	9.965
0.0820	9.73
0.0304	9.354
0.0292	8.353
0.0278	8.151

Obviously, the best option from economical point of view is the first solution on Table 5.4. While the last solution is considered as the best selection for environmental consideration. The rates corresponding to the best NPV and these corresponding to the best VIR on the Pareto front are presented in Figures 5.9 and 5.10 respectively.

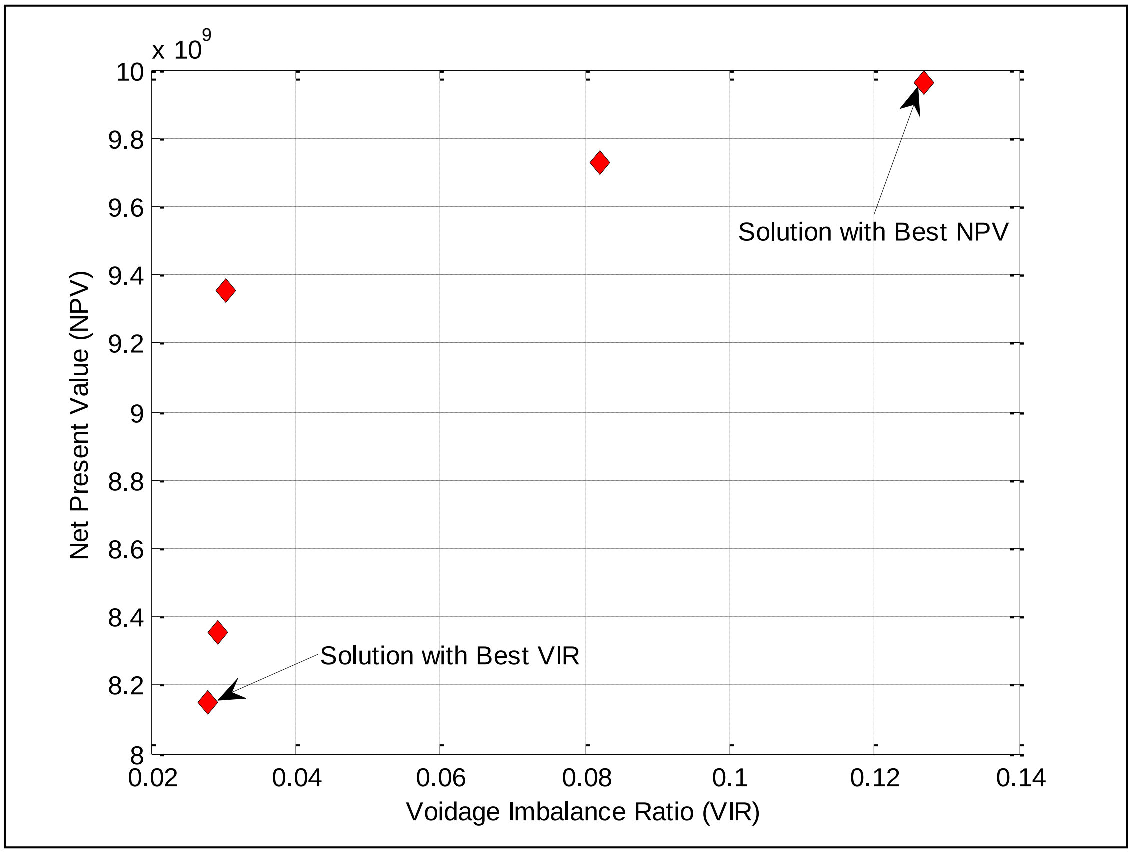

Figure 5.8: The resulted Pareto optimal set for Example 1, Scenario 2

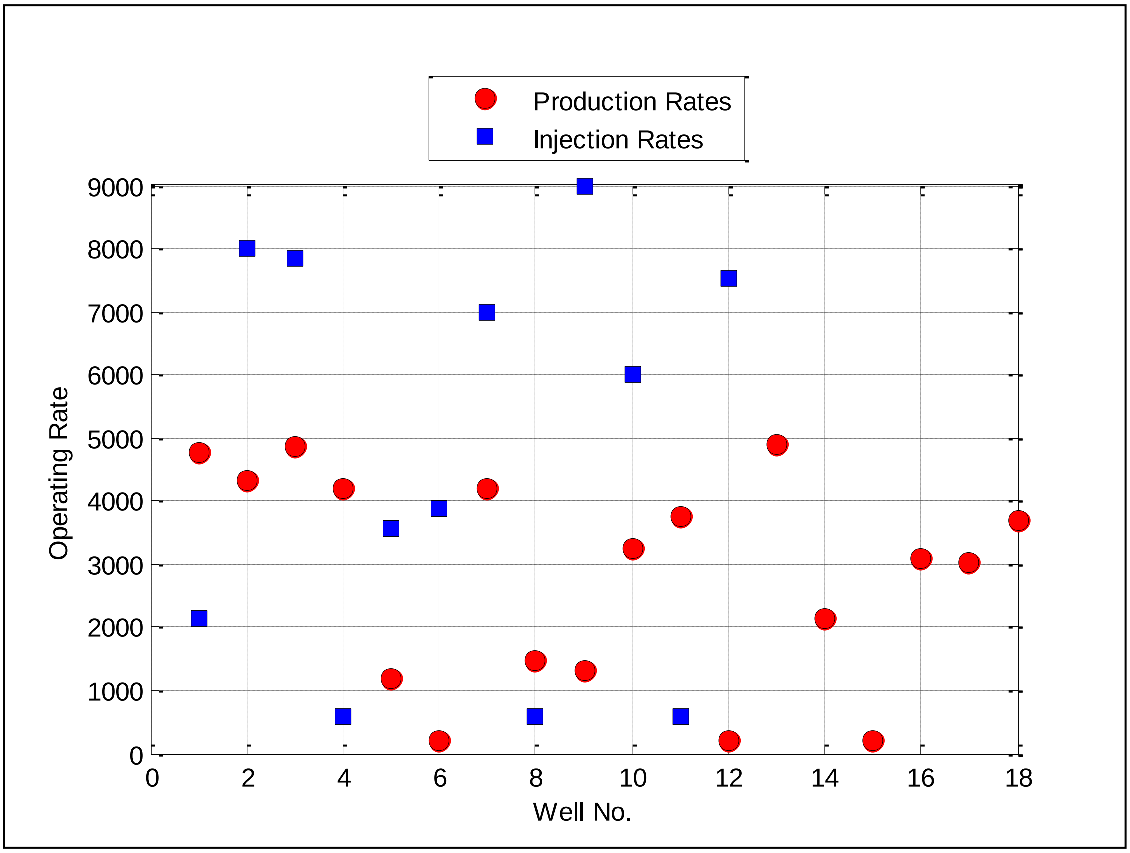

Figure 5.9: Well rates corresponding to the best NPV in the Pareto set for Example 1, Scenario 2

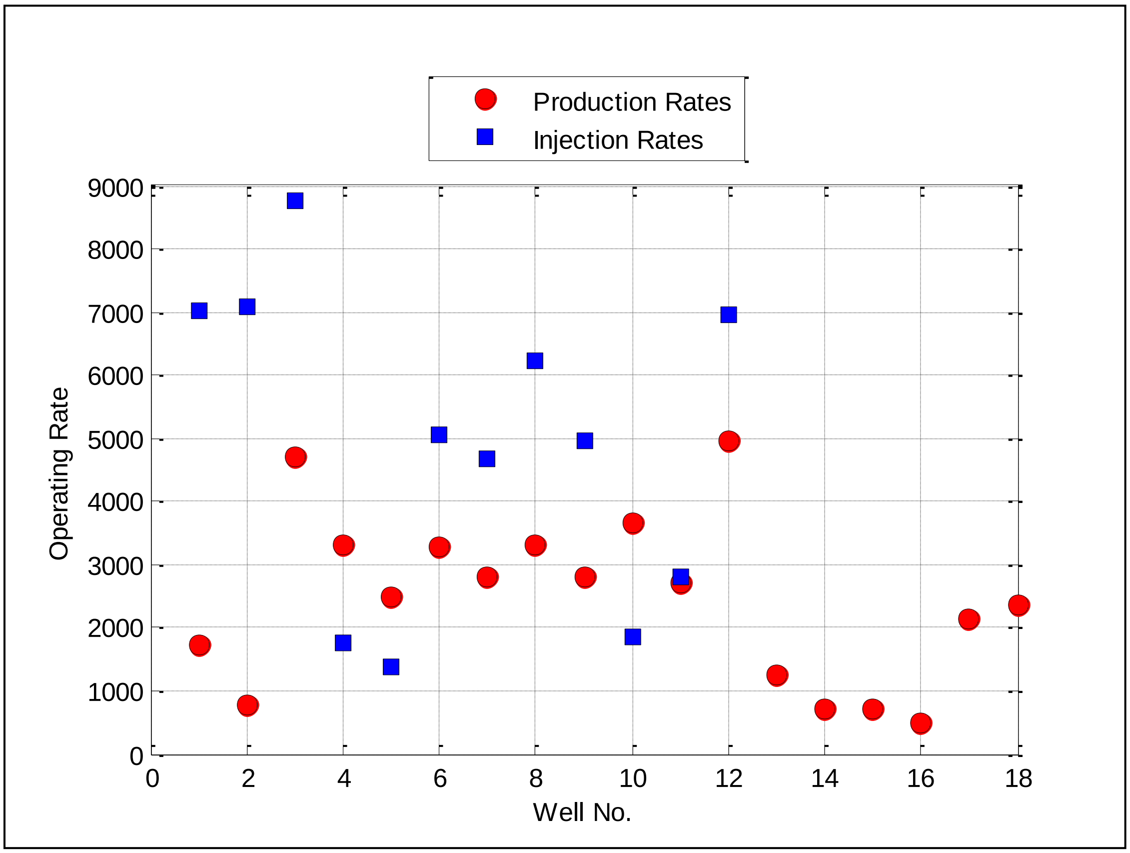

Figure 5.10: Well rates corresponding to the best VIR in the Pareto set for Example 1, Scenario 2

5.1.3 Scenario 3: Well Placement and Rate Optimization

In this scenario, both placement and operating rates for producers and injectors are optimized simultaneously. The results obtained in all cases for this scenario are presented on Table 5.5 and shown in Figure 5.11.

Table 5.5: The NPV and VIR values for base case and the four cases for Example 1, Scenario 3

	NPV $\times 10^9$	**VIR**
Base Case	3.494	0.173
NPV Only	13.15	0.1585
VIR Only	7.937	0.0022
Weighted Sum	10.27	0.006
Pareto-based (Best NPV)	11.3	0.0196
Pareto-based (Best VIR)	10.62	0.005

The Pareto-based technique optimizes both NPV and VIR without combining them and without preference for any objective. This technique provides a set of alternative solutions at once.

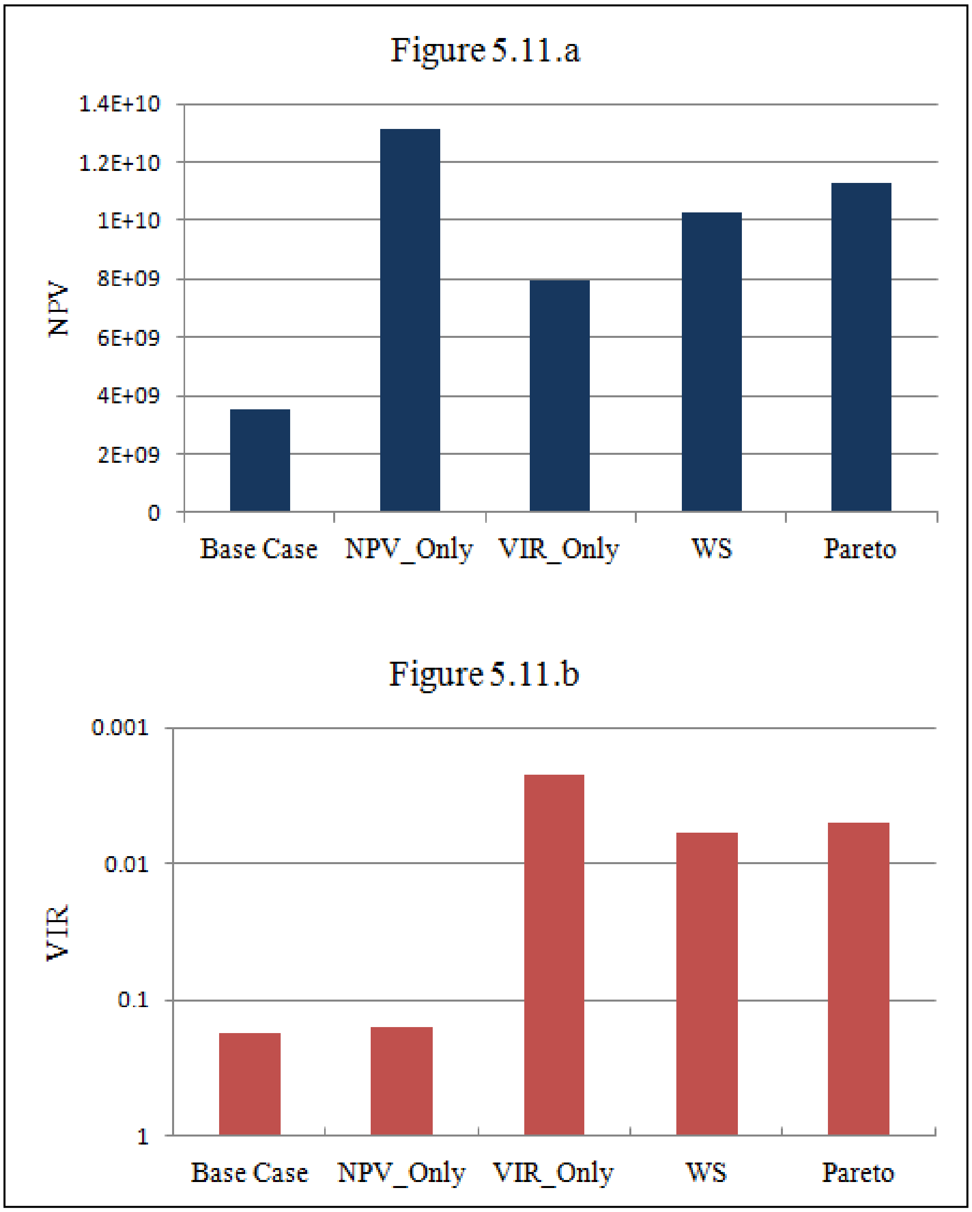

Figure 5.11: The resulted values of a) NPV and b) VIR for base case and the four cases for Example 1, Scenario 3

The obtained Pareto optimal set of joint well placement and operating rate optimization includes three superior solutions, which are shown in Figure 5.12 and the values are presented on Table 5.6. Three options of the optimized well placement and rates were obtained. Each of these three options corresponds to optimum value of NPV and VIR in some sense.

Table 5.6: The VIR and NPV values from Pareto Front for Example 1, Scenario 3

VIR	**NPV** $\times 10^9$
0.0196	11.3
0.0068	11.06
0.0049	10.62

The first solution on Table 5.6 with the best NPV value is the best solution for the investors and the corresponding well configurations and operating rates are shown in Figure 5.13. While the last solution with the minimum VIR value is the best option for the environmental aspect and the corresponding well locations and rates are shown in Figure 5.14. Figure 5.15 shows the well locations and rates corresponding to the median solution.

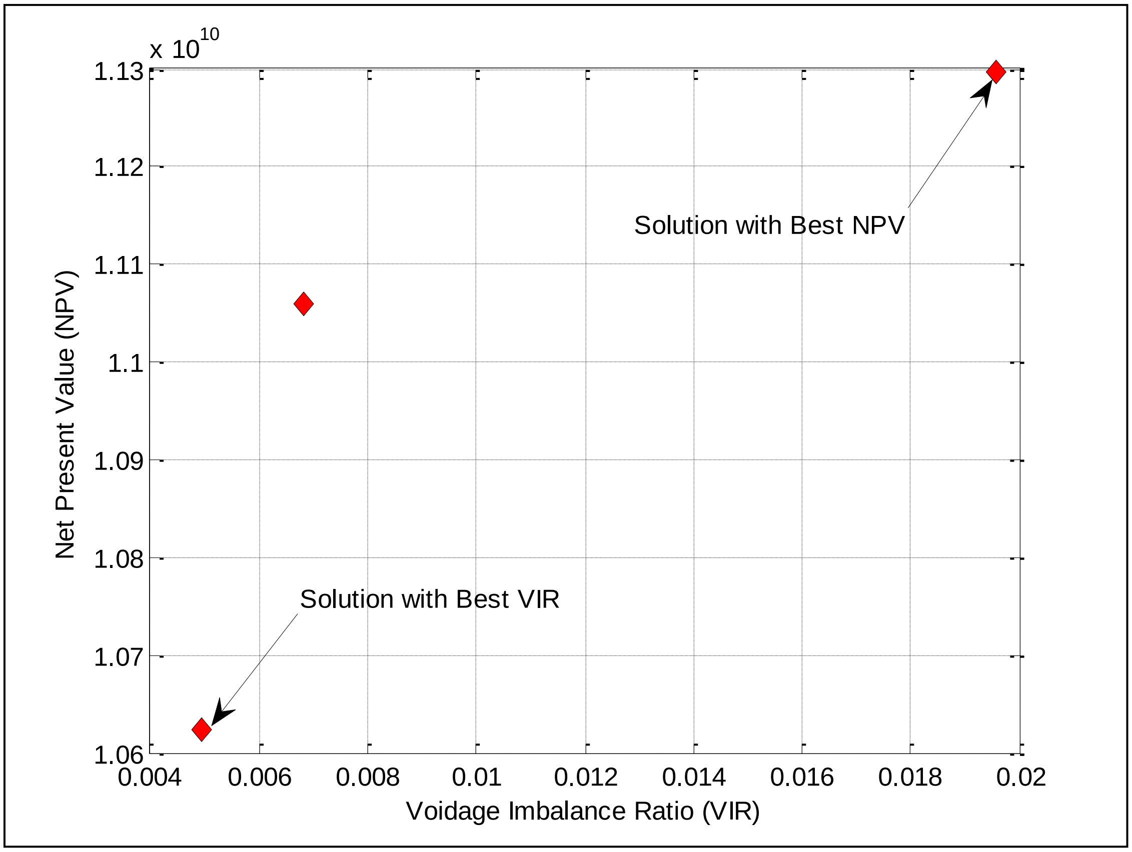

Figure 5.12: The resulted Pareto optimal set for Example 1, Scenario 3

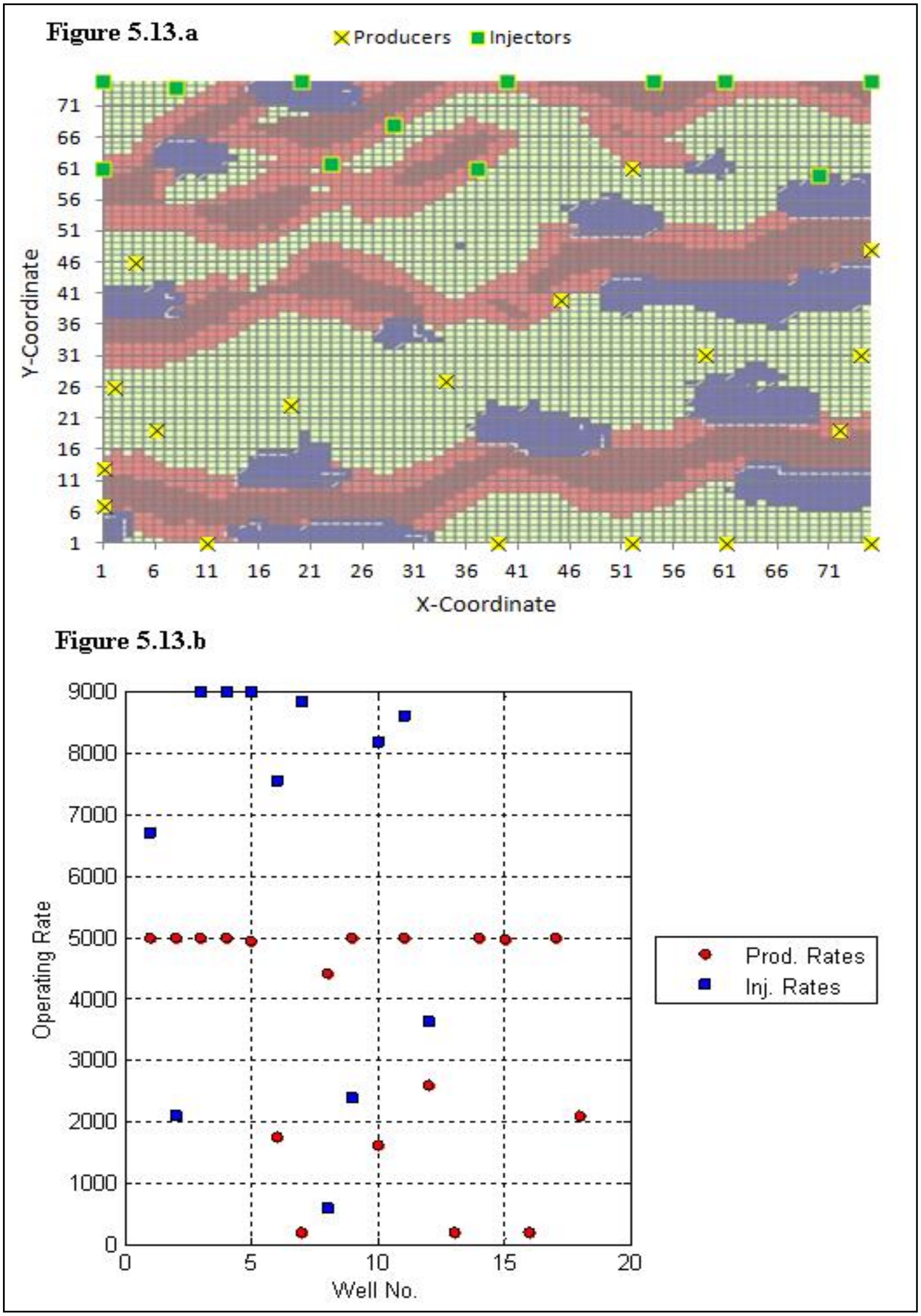

Figure 5.13: a) Well locations and b) operating rates corresponding to the best NPV in the Pareto set for Example 1, Scenario 3

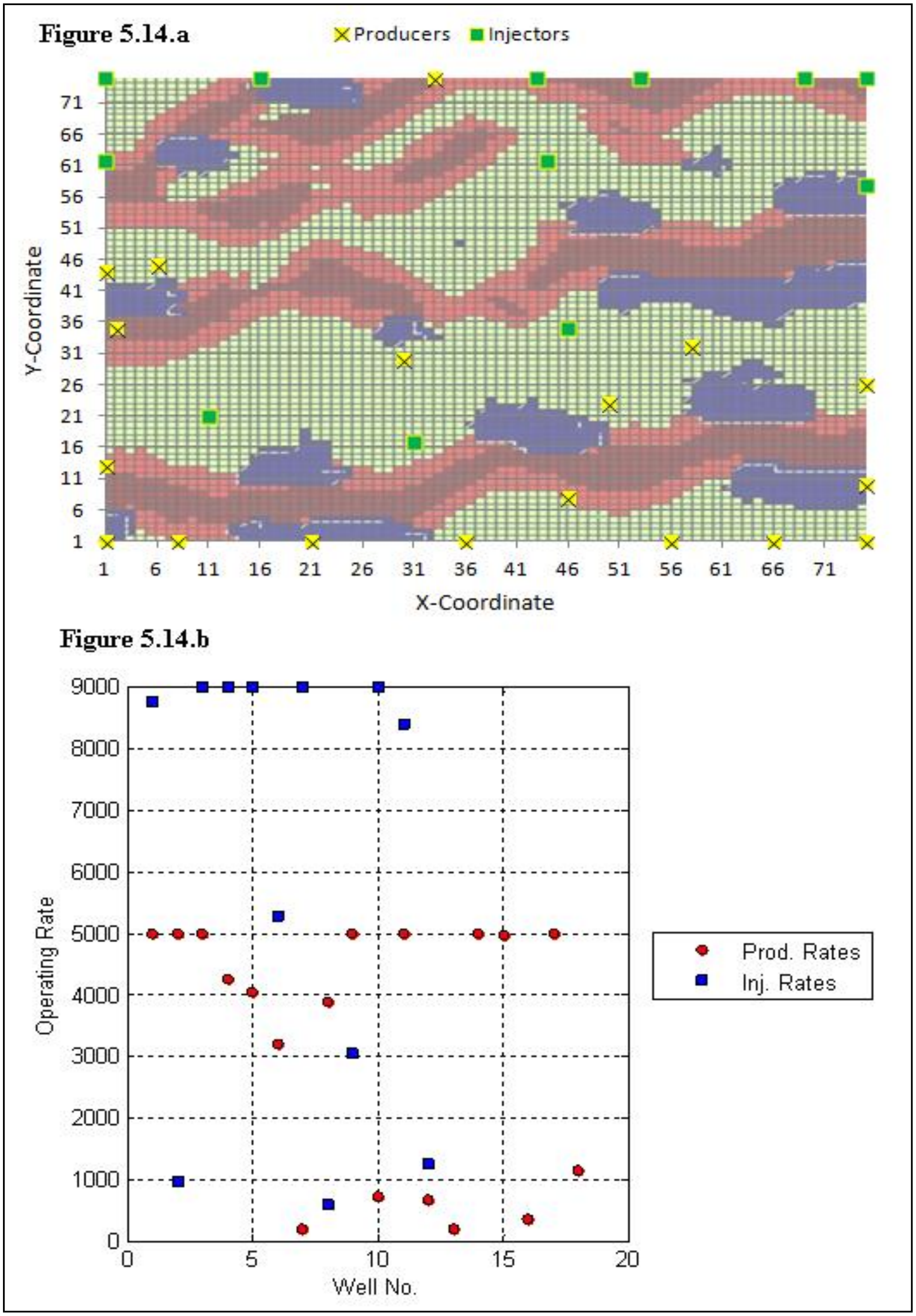

Figure 5.14: a) Well locations and b) operating rates corresponding to the best VIR in the Pareto set for Example 1, Scenario 3

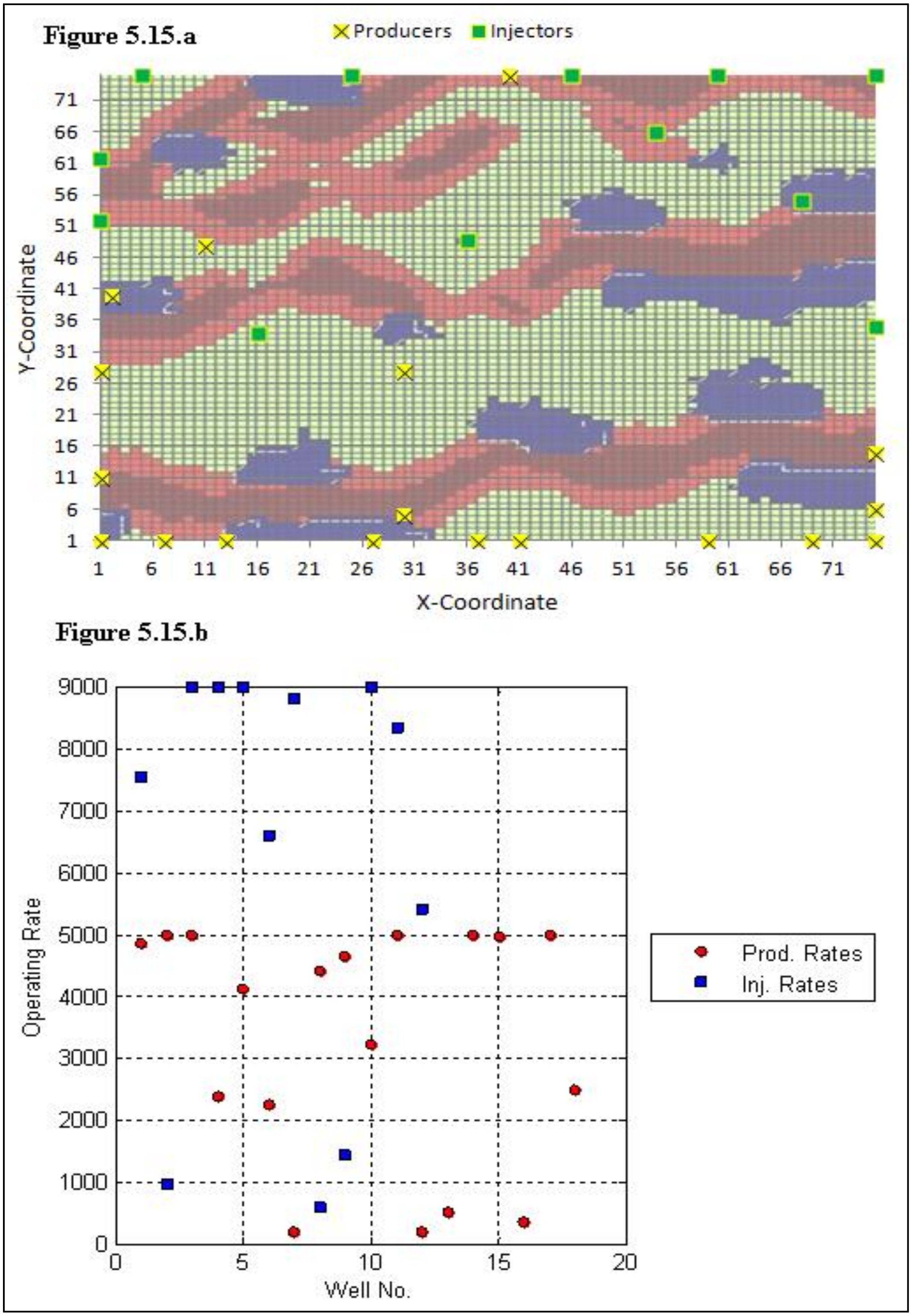

Figure 5.15: a) Well locations and b) operating rates corresponding to the median solution in the Pareto set for Example 1, Scenario 3

From the comparison between all scenarios for the channel reservoir, the optimization of coupled well placement and rate gives better results than optimizing each one individually with respect to both NPV and VIR values as shown in Figure 5.16. Table 5.7 summarizes the results of all cases for the three scenarios and the base case.

Table 5.7: Results summary for Example 1

	WPO		WRO		WPRO	
	NPV $\times10^9$	**VIR**	**NPV $\times10^9$**	**VIR**	**NPV $\times10^9$**	**VIR**
Base Case	3.494	0.173	3.494	0.173	3.494	0.173
NPV-Only	5.676	0.2219	11.47	0.2437	13.15	0.1585
VIR-Only	4.187	0.0067	6.275	0.0136	7.937	0.0022
Weighted Sum MOBJ	5.034	0.0114	8.636	0.0309	10.27	0.006
Pareto-based MOBJ	5.296	0.0098	9.965	0.0278	11.3	0.0049

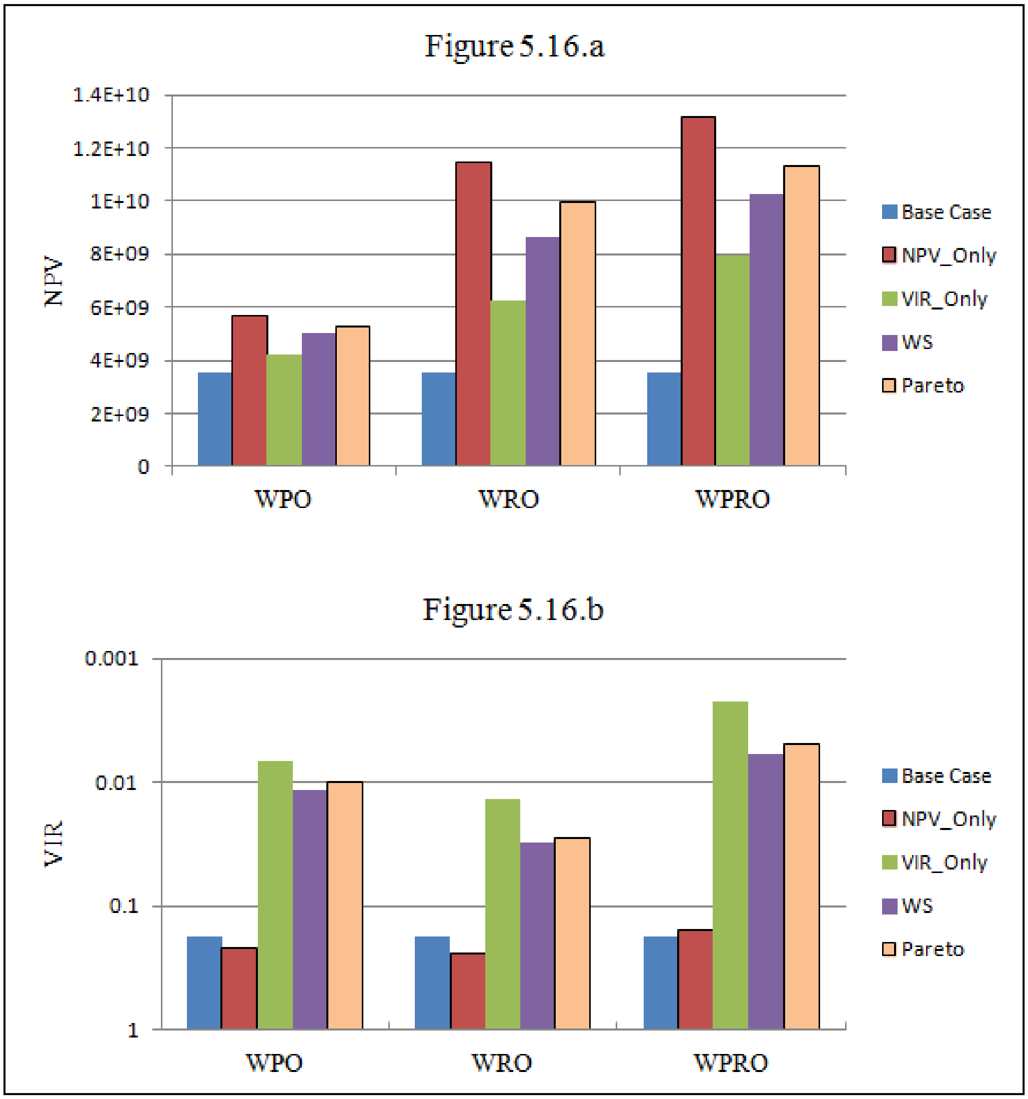

Figure 5.16: The resulted a) NPV and b) VIR for all Scenarios for Example 1

5.2 Example 2: Distributed Permeability Reservoir

5.2.1 Scenario 1: Well Placement Optimization

For the second reservoir (reservoir with fully distributed permeability field), the well locations were optimized for four cases. The results are presented on Table 5.8 and the values are shown in Figure 5.17. In the first two cases, the NPV and VIR are optimized individually, while in the third and fourth cases multiobjective optimization is considered using weighted sum and Pareto-based techniques respectively. The well configuration in the base case for this example is shown in Figure 5.18.

Table 5.8: The NPV and VIR values for base case and the four cases for Example 1, Scenario 1

	NPV $\times 10^9$	**VIR**
Base Case	2.392	0.3379
NPV Only	5.035	0.4425
VIR Only	1.448	0.0438
Weighted Sum	4.181	0.0773
Pareto-based (Best NPV)	4.792	0.2806
Pareto-based (Best VIR)	2.473	0.068

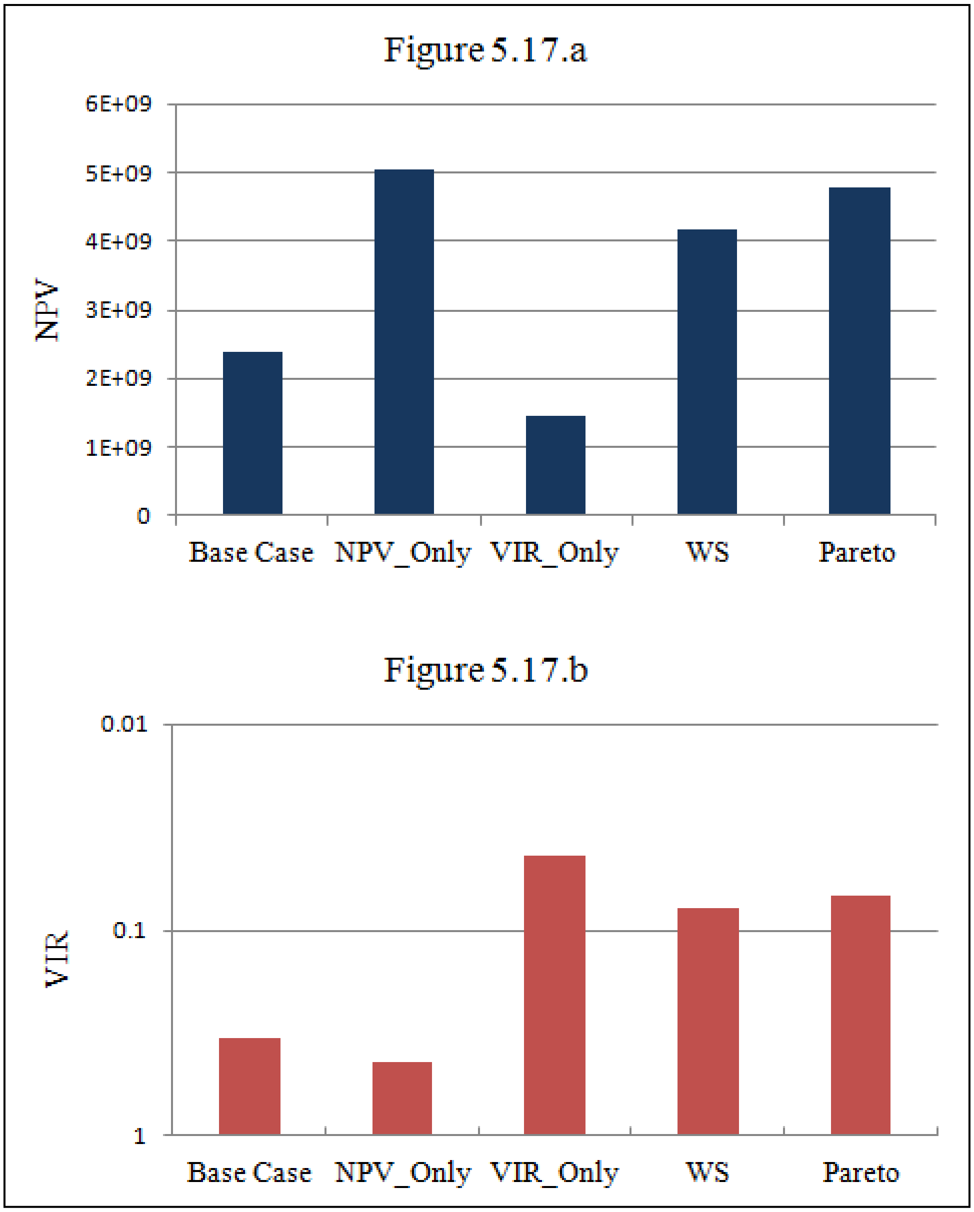

Figure 5.17: The resulted values of a) NPV and b) VIR for base case and the four cases for Example 2, Scenario 1

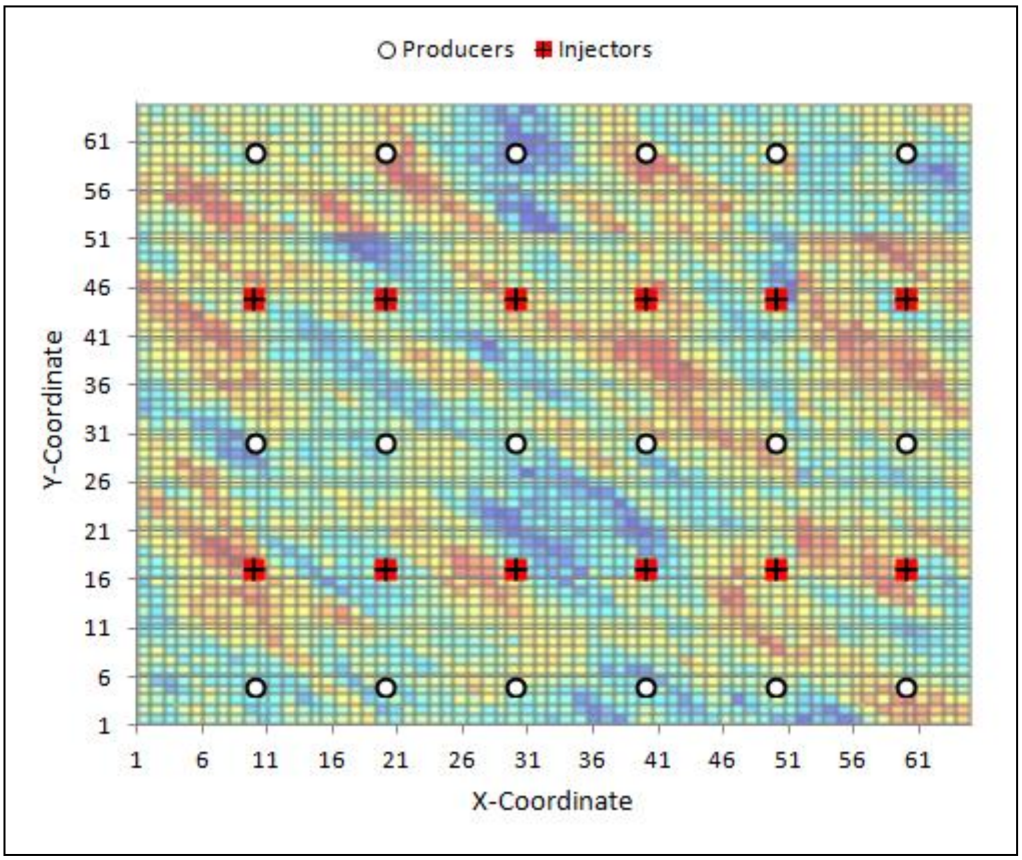

Figure 5.18: Well locations in the base case for Example 2

Using Pareto-based approach gives alternative solutions. In this case the Pareto technique generated seven superior solutions, which are shown in Figure 5.19 and the values are presented on Table 5.9. Likewise, whatever the decision-makers select, their option will be optimum because all solutions in the Pareto optimal set have evidently met the investors and environmental agencies requirements in some sense.

Table 5.9: The VIR and NPV values from Pareto Front for Example 2, Scenario 1

VIR	**NPV** $\times 10^9$
0.2806	4.792
0.2732	4.705
0.1893	4.59
0.0839	4.515
0.0749	3.8
0.0742	2.992
0.068	2.473

The first solution with the best NPV is the best option for investors while the last solution with the best VIR is the best solution for environmental agencies. However, the median solution (i.e. the forth solution on Table 5.9) has VIR close to the lowest value and NPV close to the highest value and this solution may be satisfactory to both aspects. The well locations corresponding to the solution with the best NPV, the solution with the best VIR and the median solution are shown in Figures 5.20, 5.21 and 5.22, respectively.

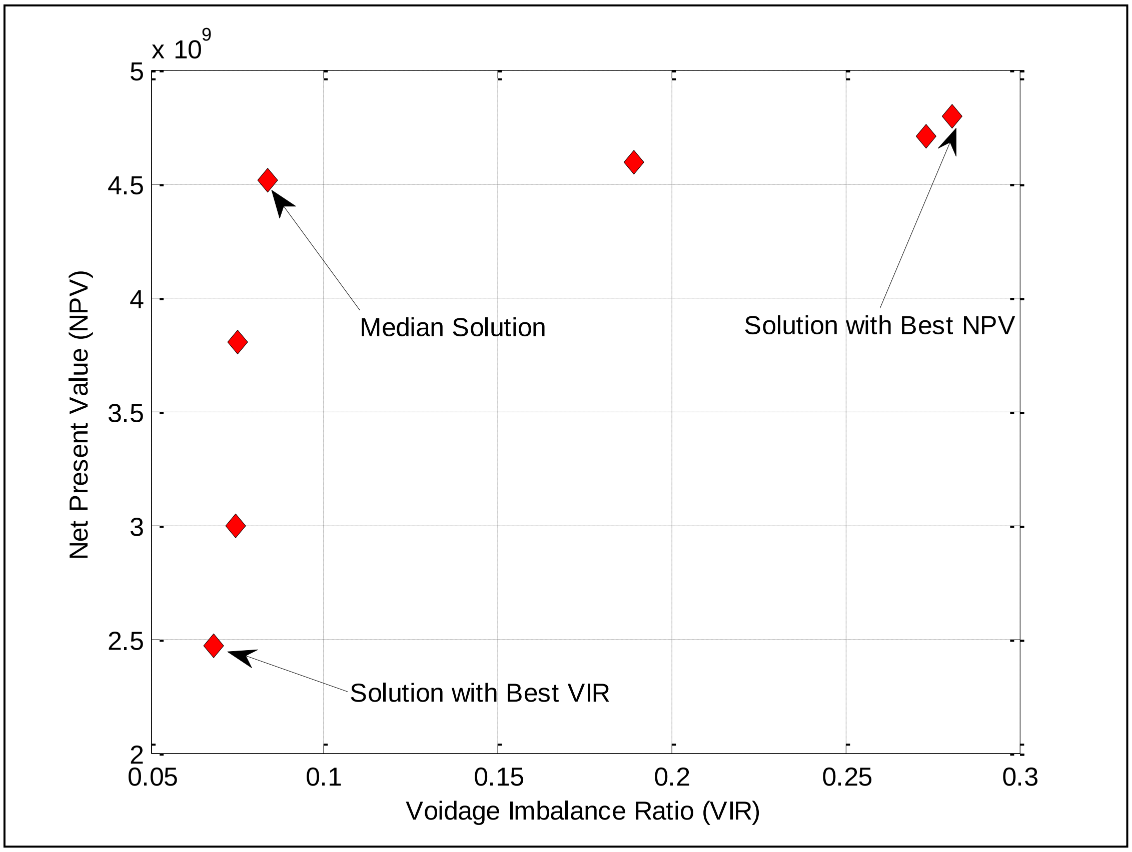

Figure 5.19: The resulted Pareto optimal set for Example 2, Scenario 1

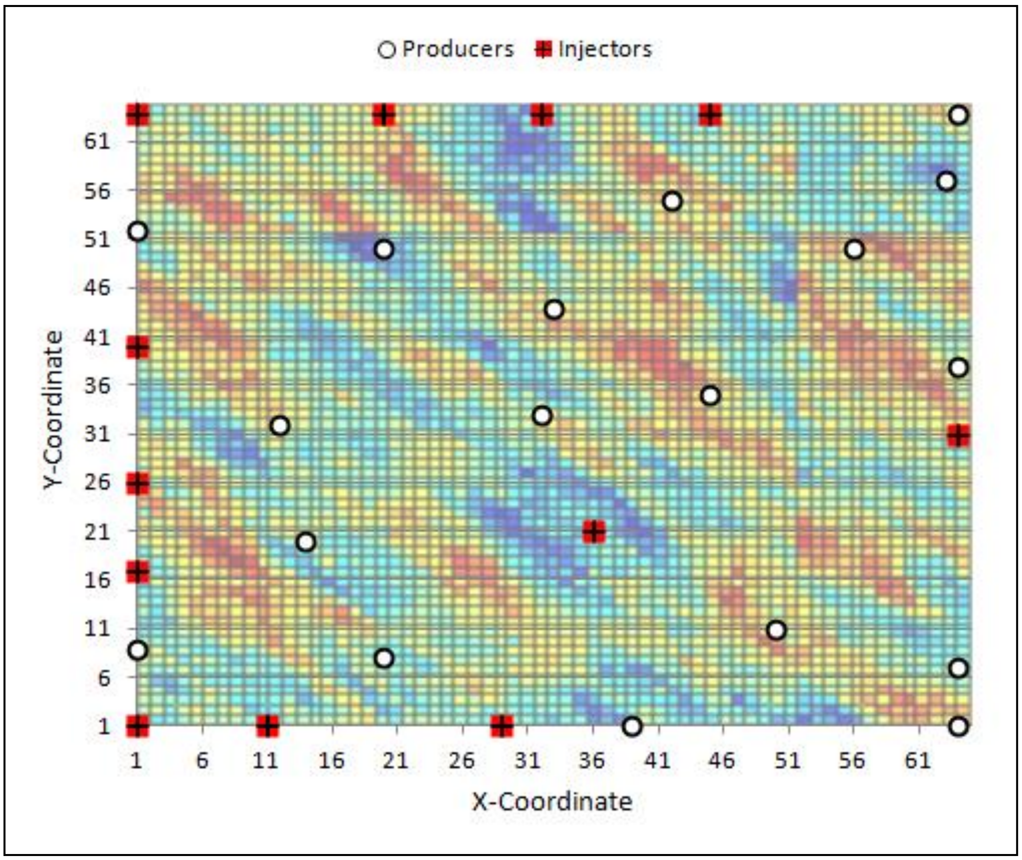

Figure 5.20: Well locations corresponding to the best NPV in the Pareto set for Example 2, Scenario 1

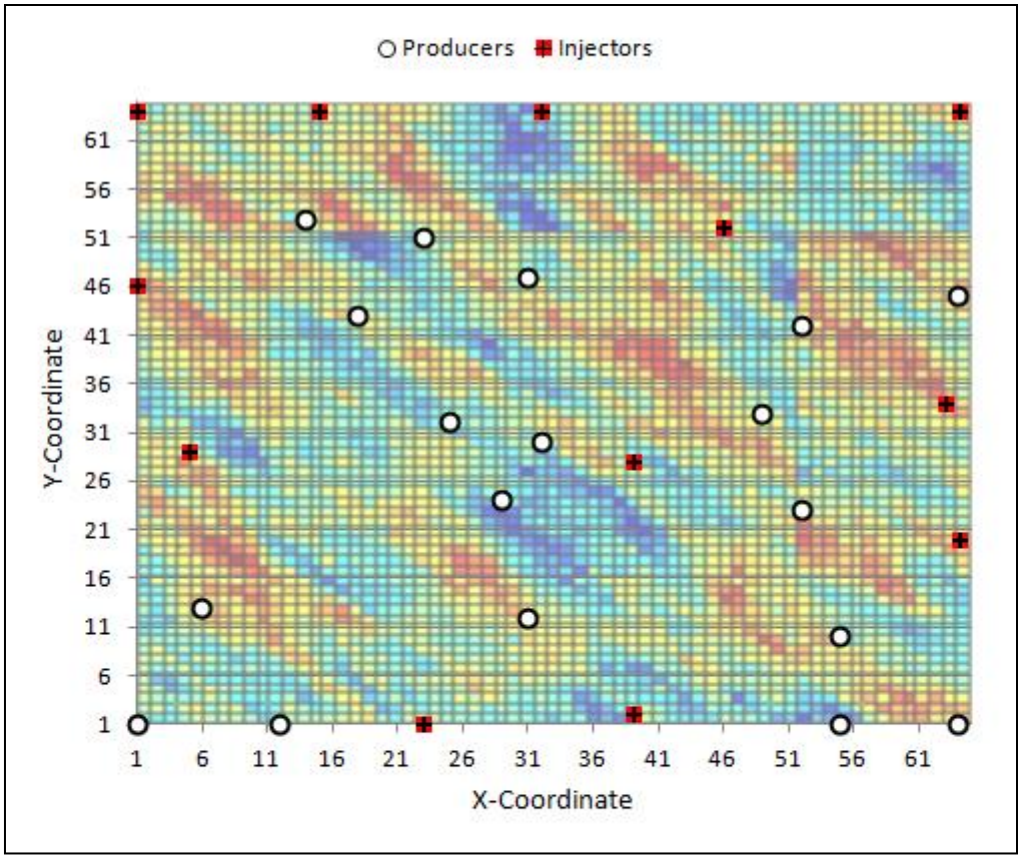

Figure 5.21: Well locations corresponding to the best VIR in the Pareto set for Example 2, Scenario 1

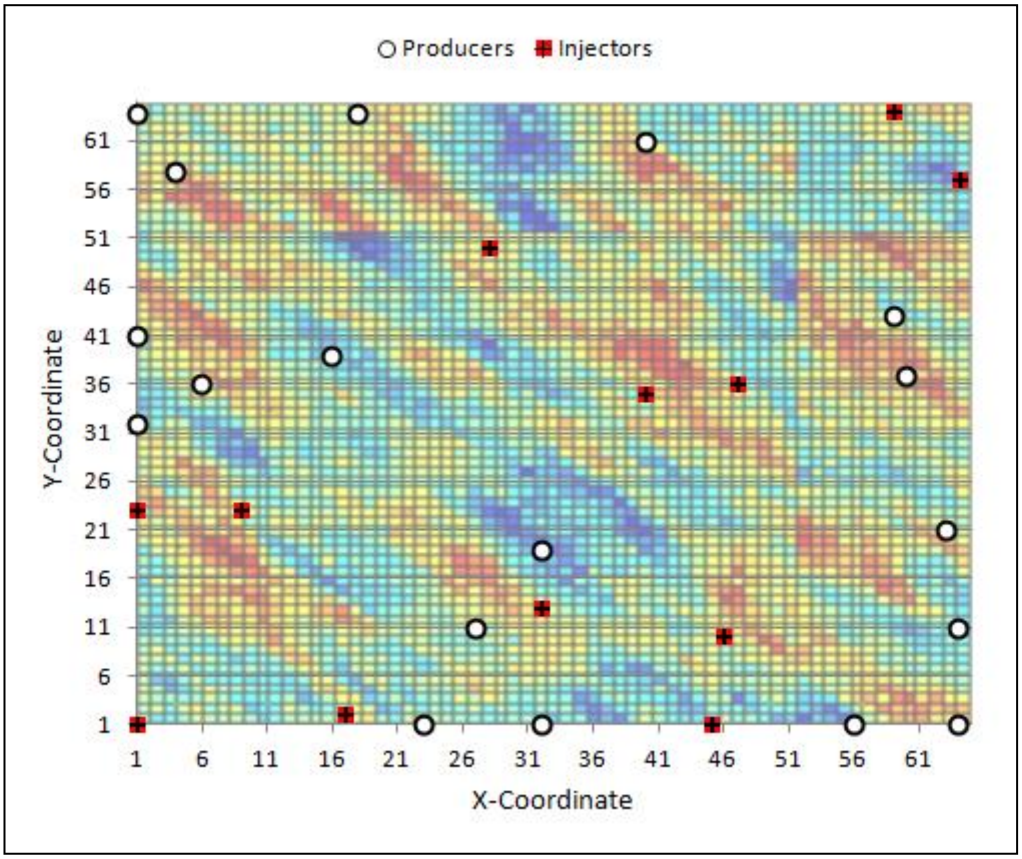

Figure 5.22: Well locations corresponding to the median solution in the Pareto set for Example 2, Scenario 1

5.2.2 Scenario 2: Well Rate Optimization

The results of the four cases for this scenario are presented on Table 5.10 and the values are shown in Figure 5.23.

Table 5.10: The NPV and VIR values for base case and the four cases for Example 2, Scenario 2

	NPV $\times 10^9$	**VIR**
Base Case	2.392	0.3379
NPV Only	9.63	0.5075
VIR Only	3.59	0.0219
Weighted Sum	8.058	0.0408
Pareto-based (Best NPV)	8.734	0.1293
Pareto-based (Best VIR)	6.355	0.0348

Similarly, using Pareto-based approach for multiobjective optimization gives multiple alternative solutions.

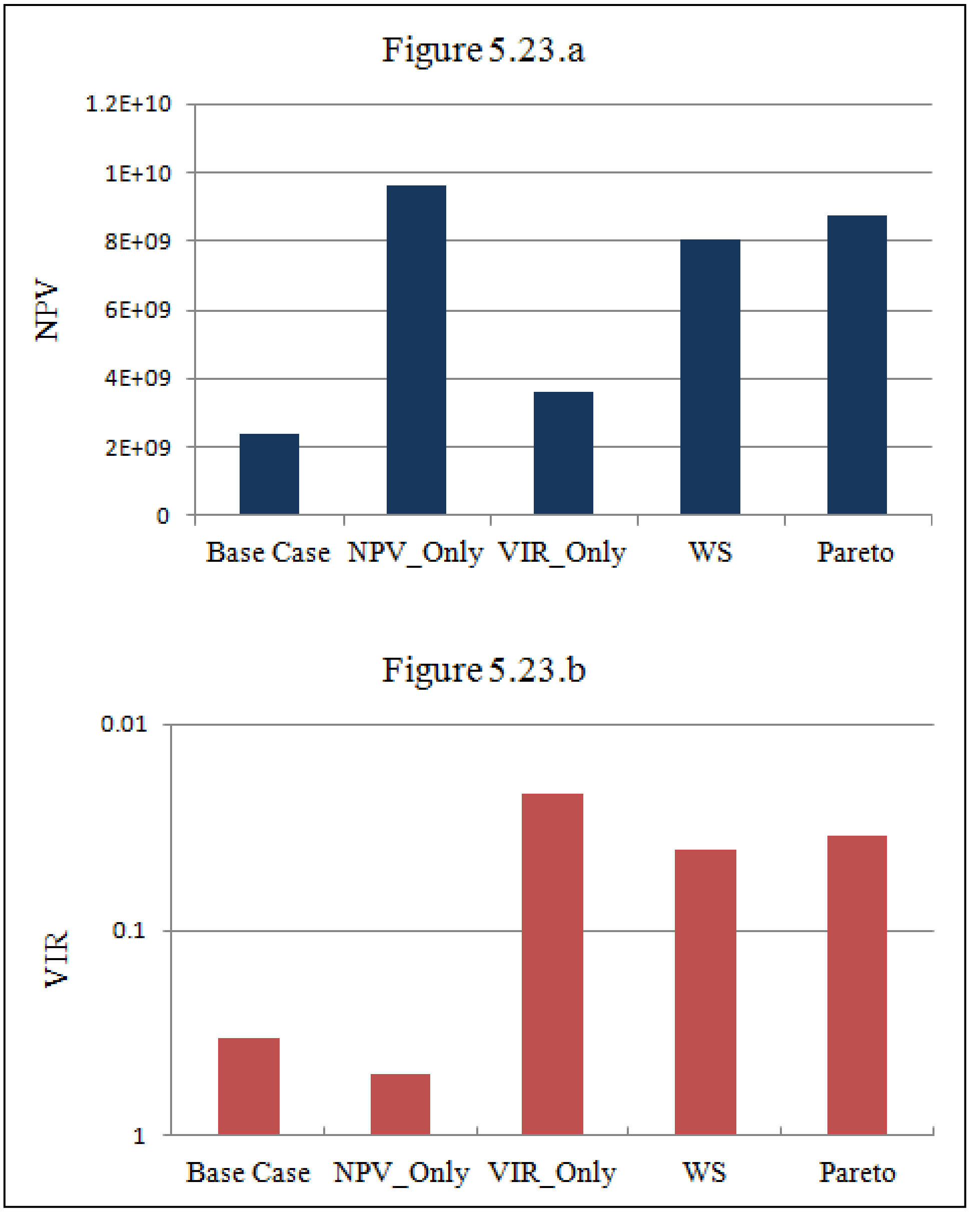

Figure 5.23: The resulted values of a) NPV and b) VIR for base case and the four cases for Example 2, Scenario 2

In this scenario, the Pareto-based approach generated five superior solutions that formed the Pareto front as shown in Figure 5.24. The NPV and VIR values of these solutions are presented on Table 5.11. All solutions are optimal in some sense for both environmental and economical criteria.

Table 5.11: The VIR and NPV values from Pareto Front for Example 2, Scenario 2

VIR	**NPV** $\times 10^9$
0.1293	8.734
0.0868	8.098
0.0578	7.694
0.0376	6.9
0.0348	6.355

The first solution with the highest NPV is the best option for the economical aspect and the corresponding well rates are shown in Figure 5.25. While the last solution with the lowest VIR value is the best option from the environmental regulatory point of view and the corresponding well rates are shown in Figure 5.26.

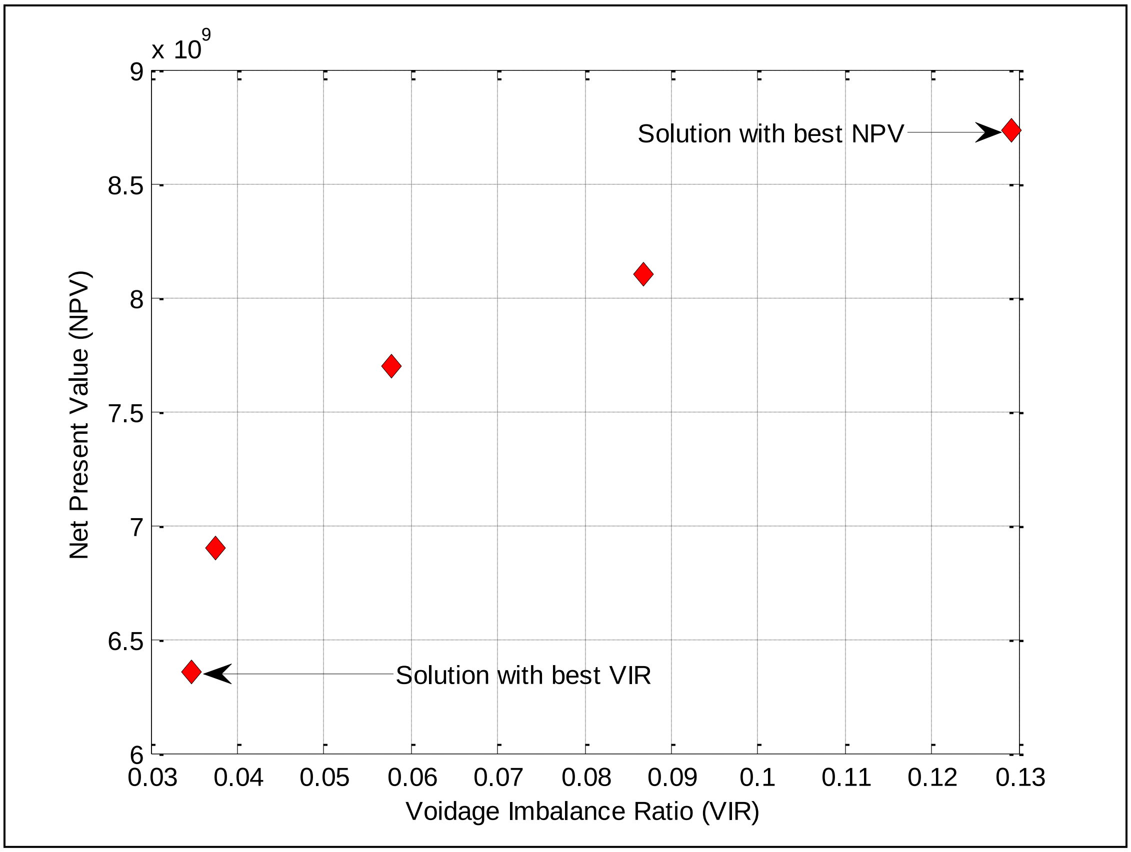

Figure 5.24: The resulted Pareto optimal set for Example 2, Scenario 2

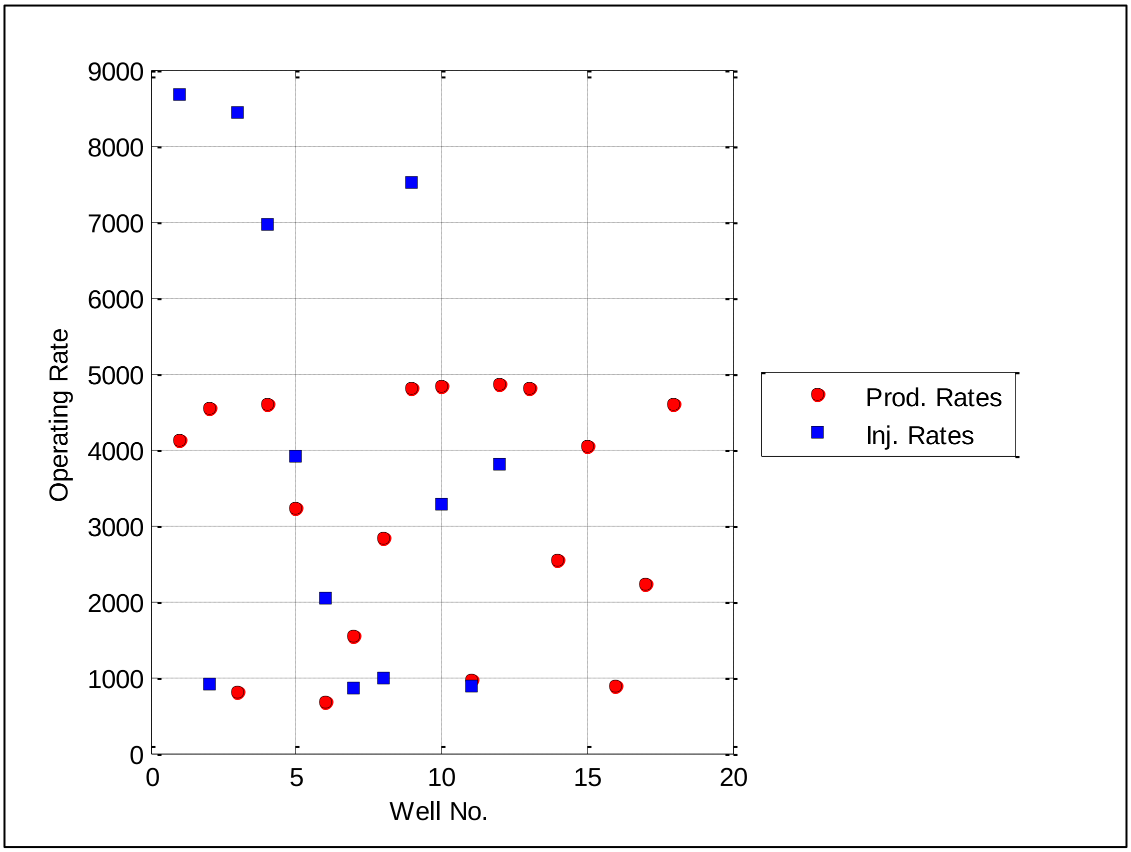

Figure 5.25: Well rates corresponding to the best NPV in the Pareto set for Example 2, Scenario 2

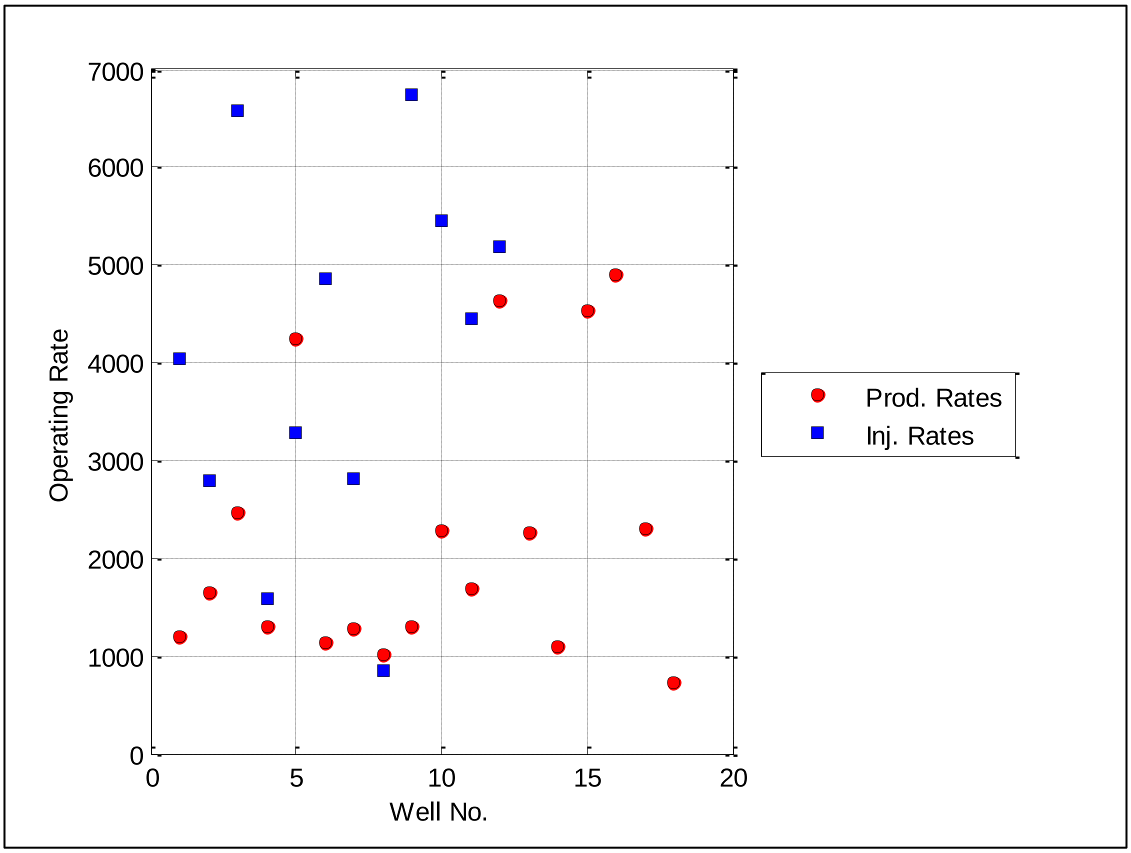

Figure 5.26: Well rates corresponding to the best VIR in the Pareto set for Example 2, Scenario 2

5.2.3 Scenario 3: Well Placement and Rate Optimization

In this scenario, locations and operating rates for producers and injectors were optimized simultaneously. The results are presented on Table 5.12.

Table 5.12: The NPV and VIR values for base case and the four cases for Example 2, Scenario 3

	NPV $\times 10^9$	**VIR**
Base Case	2.392	0.3379
NPV Only	10.32	0.2826
VIR Only	5.423	0.0157
Weighted Sum	8.933	0.0288
Pareto-based (Best NPV)	9.249	0.0932
Pareto-based (Best VIR)	7.341	0.026

Figure 5.27 shows the advantage of using the Pareto-based approach. In which, both economical and environmental aspects are considered with multiple alternative solutions.

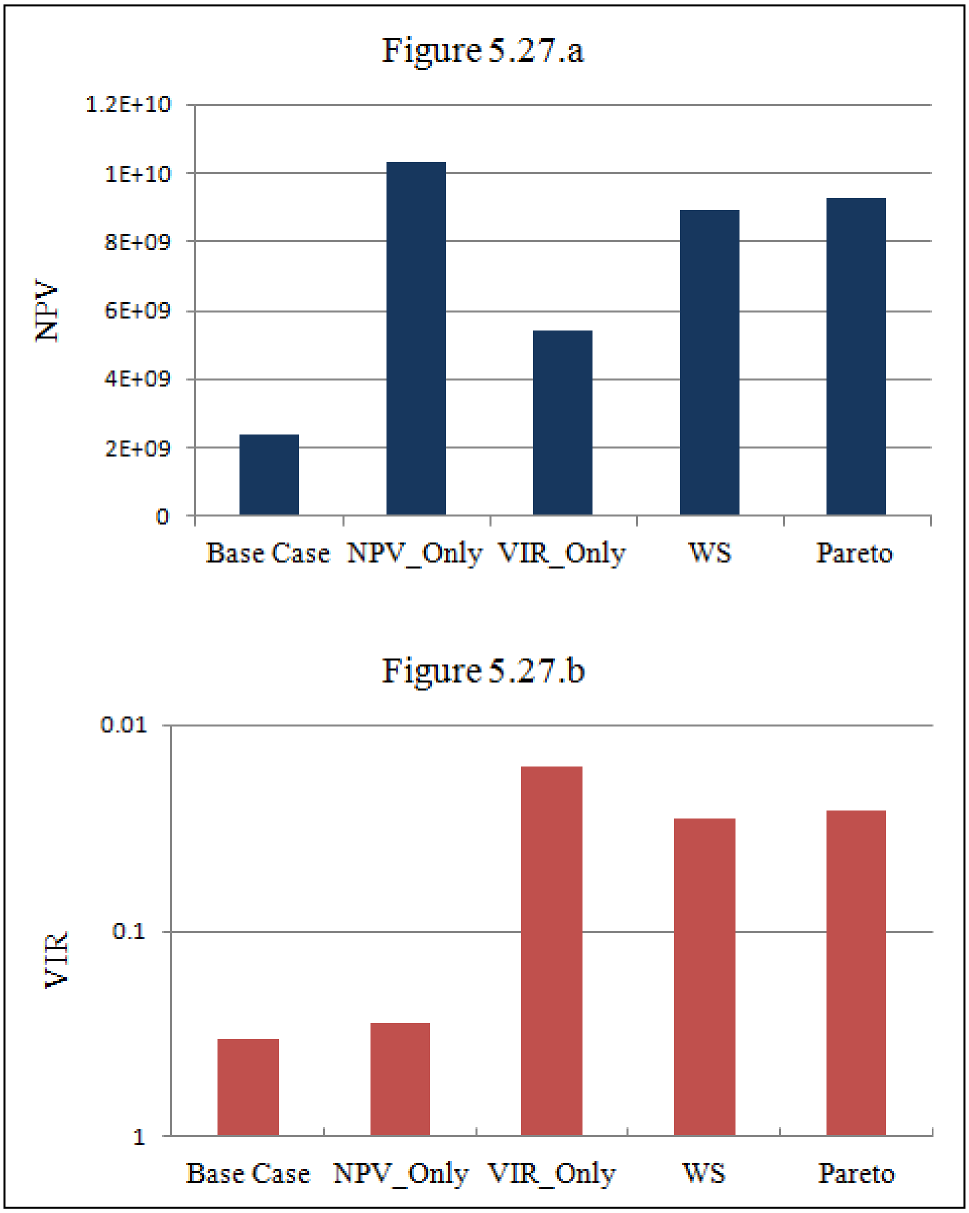

Figure 5.27: The resulted values of a) NPV and b) VIR for base case and the four cases for Example 2, Scenario 3

The Pareto Front of this scenario has six superior solutions, which are shown in Figure 5.28. The values are presented on Table 5.13. All these solutions are superior in some sense, guaranteeing the optimality of whatever the decision maker's option.

Table 5.13: The VIR and NPV values from Pareto Front for Example 2, Scenario 3

VIR	**NPV** $\times 10^9$
0.0932	9.249
0.0589	9.204
0.0496	8.938
0.0409	8.455
0.03	7.568
0.026	7.341

The first solution is the best option for the investors while the last solution is the best option for the environmental aspect. Obviously, the Pareto optimal set has met the investors and environmental agencies requirements and has provided different options for the decision makers. Figures 5.29, 5.30 and 5.31 show the well configurations and rates corresponding to the solution with the best NPV, the solution with the best VIR and median solution, respectively.

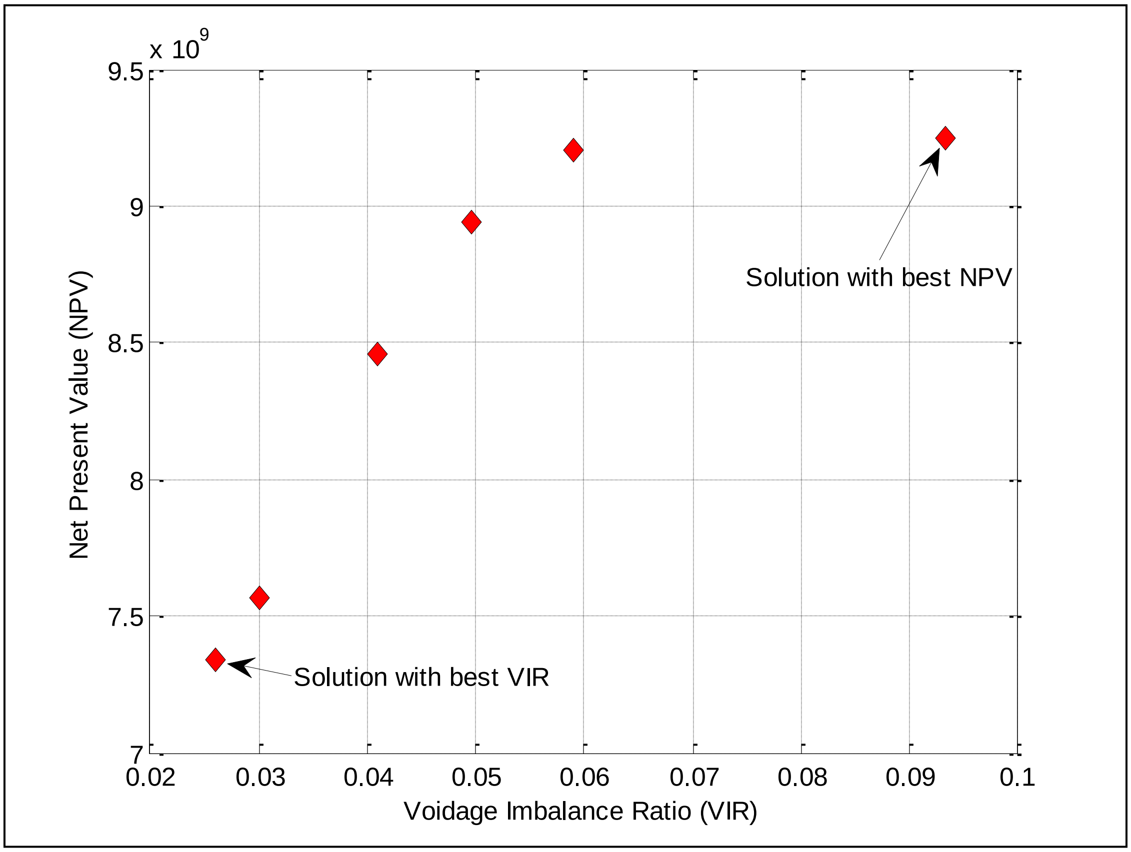

Figure 5.28: The resulted Pareto optimal set for Example 2, Scenario 3

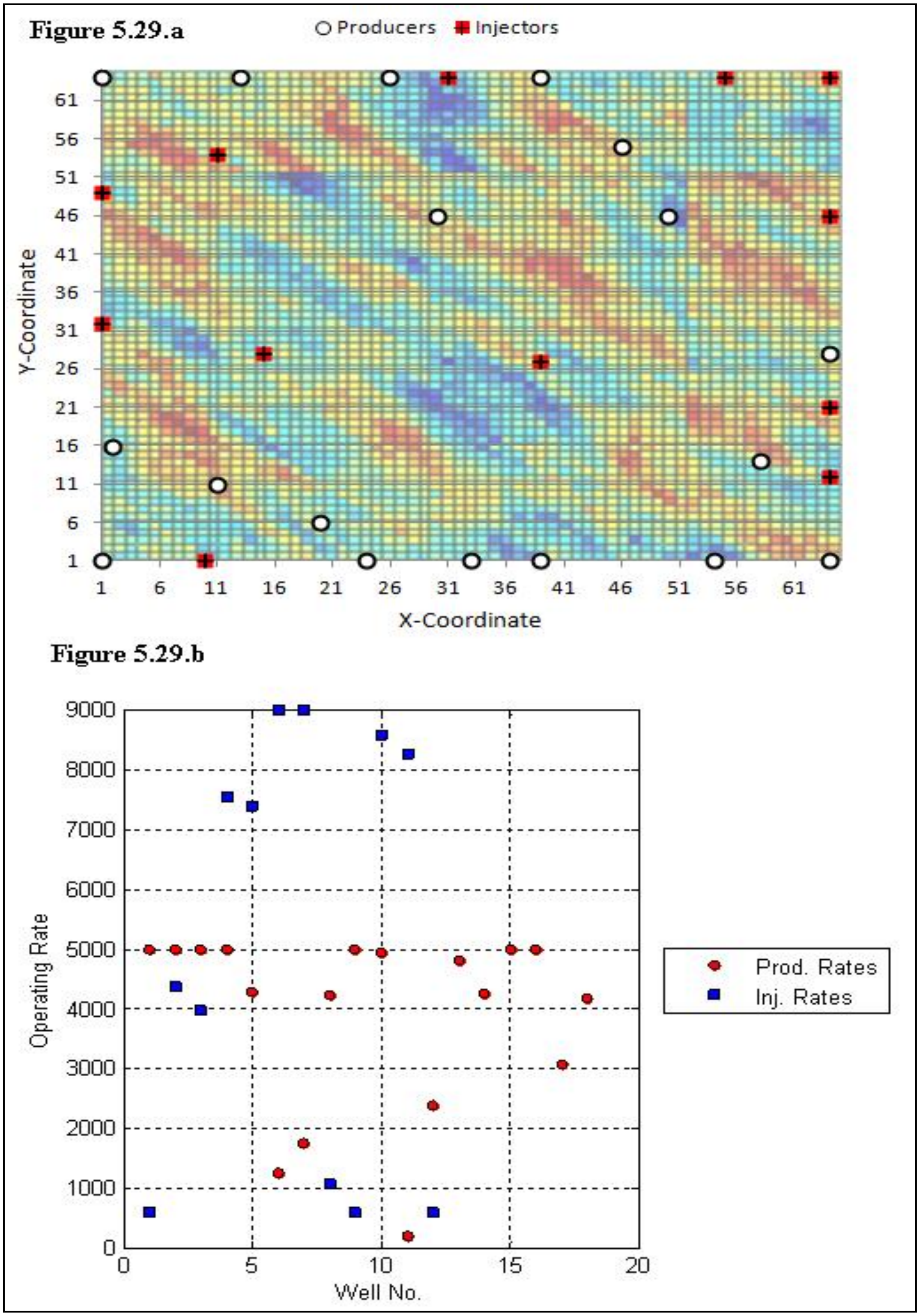

Figure 5.29: a) Well locations and b) rates corresponding to the best NPV in the Pareto set for Example 2, Scenario 3

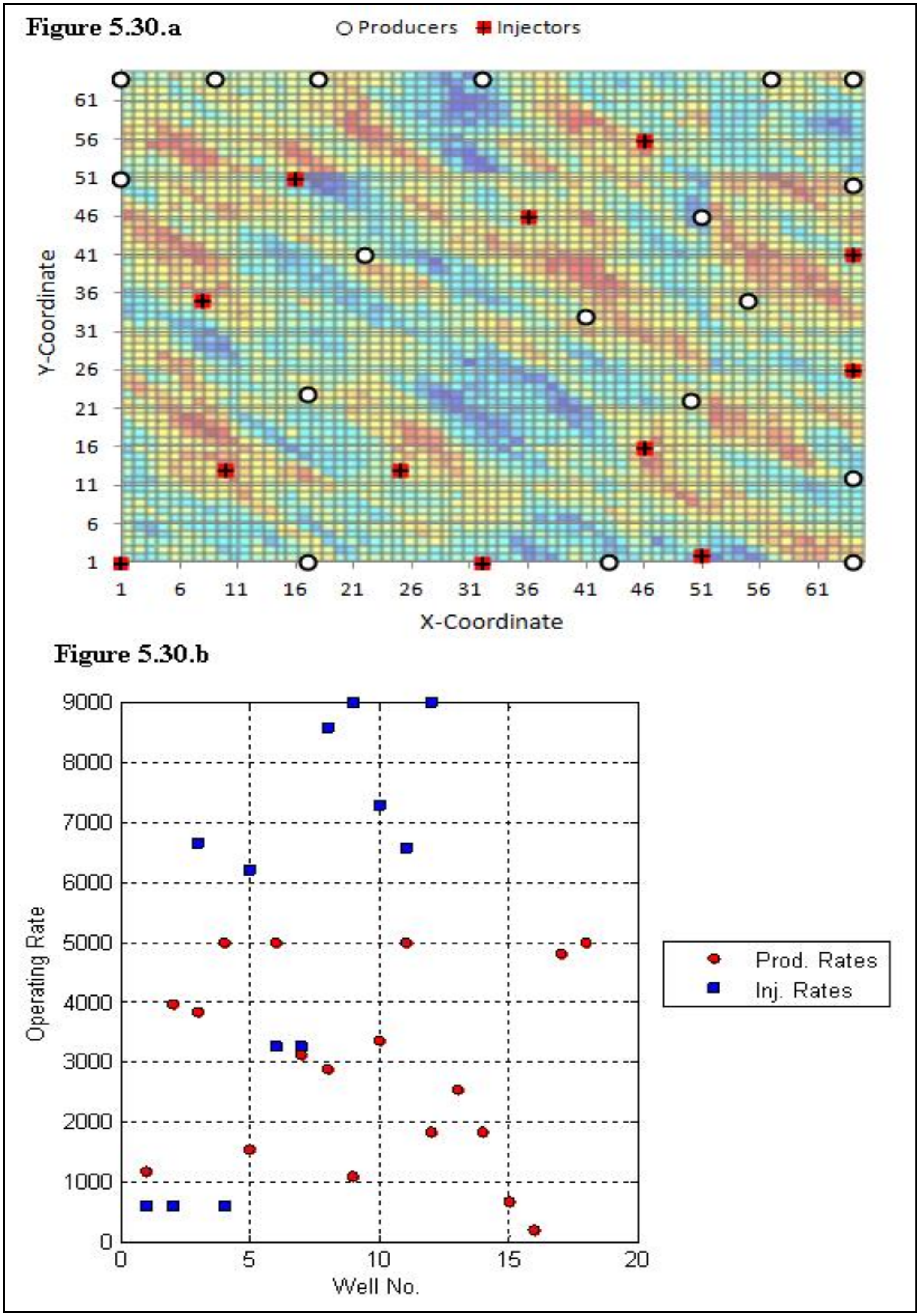

Figure 5.30: a) Well locations and b) rates corresponding to the best VIR in the Pareto set for Example 2, Scenario 3

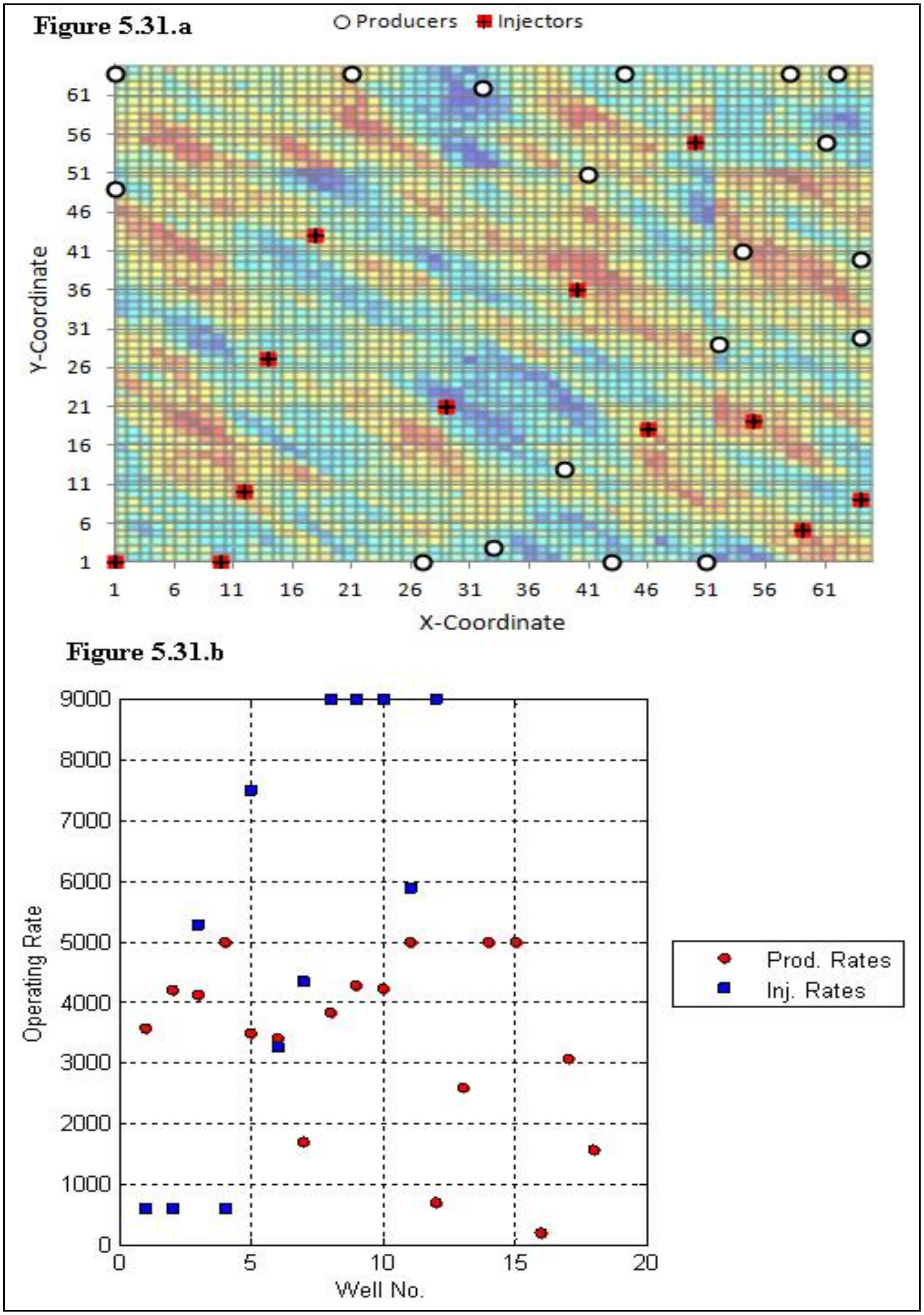

Figure 5.31: a) Well locations and b) rates corresponding to the median solution in the Pareto set for Example 2, Scenario 3

Similar to Example 1, the comparison between all scenarios proved that, the optimization of coupled well placement and rate gives better results than optimizing each one individually with respect to both NPV and VIR values as shown in Figure 5.32. Table 5.14 summarizes the results of all cases for the three scenarios and the base case.

Table 5.14: Results summary for Example 2

	WPO		**WRO**		**WPRO**	
	NPV $\times 10^9$	**VIR**	**NPV** $\times 10^9$	**VIR**	**NPV** $\times 10^9$	**VIR**
Base Case	2.392	0.3379	2.392	0.3379	2.392	0.3379
NPV-Only	5.035	0.4425	9.63	0.5075	10.32	0.2826
VIR-Only	1.448	0.0438	3.59	0.0219	5.423	0.0157
Weighted Sum MOBJ	4.181	0.0773	8.058	0.0408	8.933	0.0288
Pareto-based MOBJ	4.792	0.068	8.734	0.0348	9.249	0.026

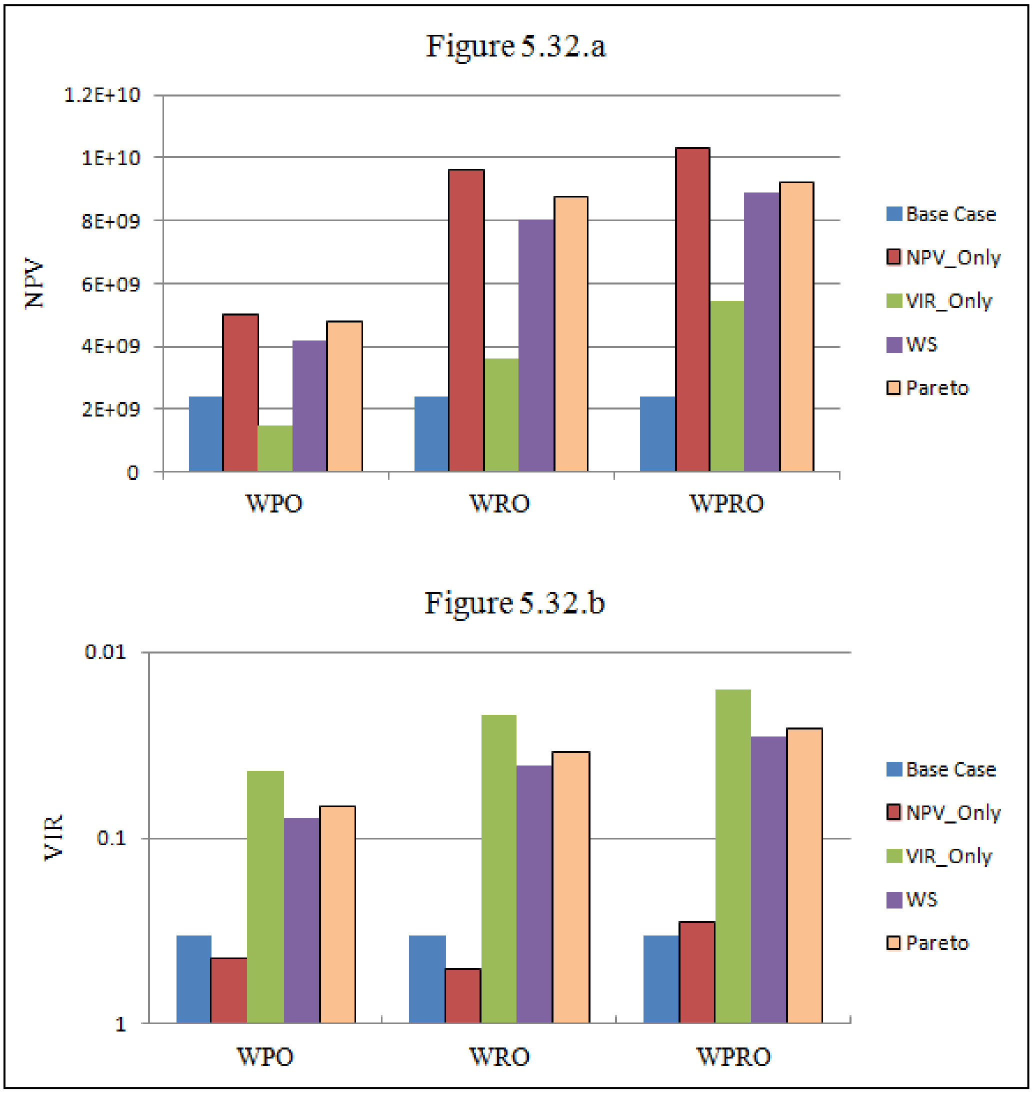

Figure 5.32: The resulted a) NPV and b) VIR for all Scenarios for Example 2

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

The integration between multiobjective differential evolution algorithm and Pareto rank was applied in three scenarios: the first is to find only the optimum well placement, the second scenario is to optimize the well operating rate only, while the third scenario is to couple well placement and rate optimization. All these scenarios were tested on two synthetic examples: channeled reservoir and a reservoir with fully distributed permeability field. In each scenario, the solutions of the Pareto-based technique were compared with the results of the weighted sum technique and single objective optimization. The NPV and the VIR were optimized simultaneously to obtain the Pareto optimal front. The results proved the success and usefulness of the proposed approach and generated a set of alternative solutions; all these solutions were optimum in some sense from both economical and environmental point of view and guaranteed a balance between ensuring profitability of investment and keeping to environmental regulations in field development planning. From the comparison between all scenarios, the optimization of coupled well placement and rate gave better solutions than optimizing each one individually.

6.2 Recommendations

In this work, fixed variables were used in the NPV calculations and the study was applied to vertical wells. To advance this research, it is recommended to use variables costs and prices that vary with time. Also horizontal and multilateral wells can be used instead of vertical wells in accordance with the development in the oil industry. In addition, this research can be extended to define the optimum variable operating rates for wells in the entire field life as well as the optimum required number of production and injection wells can be included.

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